© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1714865

Adaptive Strata Selection in Parametric Histogram Equalization for Detail-Preserving Enhancement

DR. V. SESHA SRINIVAS[1], J. NIKHIL RAJ[2], A. TEJAGNA CHANDRA KARTHIKEYA[3], CH. K. BHANU PRADEEP[4], A. BLESSY BHAVINI BEENAL[5]
[1, 2, 3, 4, 5]Department of IT, RVR & JC College of Engineering, Guntur, Andhra Pradesh, India.

Abstract—A new adaptive contrast enhancement method based on Adaptive Strata Selection in Parametric Histogram Equalization (ASPHE) is proposed to adaptively select the stratification parameters according to the image content for robust contrast enhancement. Unlike the conventional SPOHE method based on the fixed stratification parameters determined empirically, the proposed ASPHE method uses the local complexity score based on the variance, entropy, and gradient information of each image region to adaptively select the number of strata. To efficiently compute the local complexity score of each image region, the integral image is employed. An adaptive mapping function is designed to guarantee the image regions with higher complexity are stratified finely while those with smoother image content are stratified coarsely. The proposed adaptive strategy has been demonstrated to enhance image contrast while avoiding the occurrence of artifacts like halos, blocking effects, and over-enhancement. The experimental results have demonstrated the ability of ASPHE to achieve an accurate approximation of the cdf while offering better adaptability to various images with efficient computation compared to the SPOHE method.

Index Terms— Contrast Enhancement, Histogram Equalization, Adaptive Parameter Selection, Image Enhancement, Stratified Sampling.

I. INTRODUCTION

One of the most common image processing goals is image enhancement. Image enhancement is a traditional image processing problem with the objective of improving the visual perception of an image for both human and machine vision systems. Image enhancement is an image processing tool used in various domains like medical imaging, surveillance systems, remote sensing systems, and image processing for photography and document analysis. Among the various image processing methods for image enhancement, contrast enhancement is one of the basic methods for image processing.

Histogram Equalization is the most commonly used contrast enhancement method. It is based on the principle of distributing the pixels of an image over the entire range of possible intensity levels. This method is easy to implement and has achieved significant recognition. However, the basic HE method has some limitations like changes in the image brightness level, unnatural image tones, and artifacts like over-enhancement and saturation. This has given rise to various HE methods like Dynamic Histogram Equalization for maintaining the overall image brightness level, RSWHE for avoiding over-enhancement of the image, and AHE for local image details. Other HE methods like BBHE, DSIHE, and MMBEBHE are based on the principle of maintaining the overall image brightness level. Other methods like RMSHE are based on the principle of recursive decomposition for local image contrast enhancement. All these methods have some limitations like visual artifacts, unnatural image tones, and high computational complexity.

Apart from HE methods, image processing methods like morphological image processing have also been used for image contrast enhancement. This is based on the principle of estimating the image background for image contrast enhancement. Image Background Approximation by Blocks and Image Background Determination using Opening by Reconstruction are the morphological image processing methods developed for image contrast enhancement. These methods have been developed to handle illumination changes. Recently, the MOR image processing method has been developed for image contrast enhancement. This method is based on the principle of introducing a new parameter for avoiding over-illumination.

To overcome the limitations of histogram-based and morphology-based image enhancement techniques, a technique called Parametric-Oriented Histogram Equalization (POHE) was proposed. The technique uses Gaussian modeling to approximate the intensity distribution in images. However, it suffers from the disadvantage that it is a unimodal technique and hence produces halos in images. Stratified Parametric-Oriented Histogram Equalization (SPOHE) was proposed as an improvement to the above technique by incorporating the theory of stratified sampling to achieve a better representation of the Gaussian model of image intensity distribution. The technique performs image enhancement without any artifacts and with low computational complexity while preserving the brightness of the image. However, in the above technique, the use of fixed parameters in stratified sampling might not be efficient in handling different types of images.

Adaptive Strata Selection in Parametric Histogram Equalization: In order to overcome the limitations of the above technique, a technique called Adaptive Strata Selection in Parametric Histogram Equalization (ASPHE) was proposed. The technique uses an adaptive parameter estimation mechanism that uses image statistics to achieve image enhancement. The technique is different from Stratified Parametric-Oriented Histogram Equalization in that it uses an adaptive parameter estimation mechanism to achieve image enhancement. The technique is efficient in achieving image enhancement as it:
- Effectively enhances dark and bright areas in images while maintaining their natural appearance.
- Suppresses various types of artifacts that are common in images.
- Is efficient in handling various types of images.

II. HE TECHNIQUES

A. Histogram Equalization

HE is a fundamental technique for increasing the contrast of an image by increasing the dynamic range of the input image by remapping the gray levels based on global statistics. This is achieved by computing the Cumulative Distribution Function (CDF) from the histogram of the image. In this context, the basic level transformation function, $f(k)$, maps the input gray level X_k to the enhanced output y_k using the scaled CDF:

$$f(k)=X_0+(X_{L-1}-X_0)\cdot c(k) \qquad (1)$$

GHE is weak in the aspect of computation but has some significant statistical and visual errors. The major problem is the mean shift problem. This is where the average value of the output image is shifted significantly compared to the average value of the input image. It also has the problem of creating artifacts because of the dominance of high-frequency levels of intensity. This is where the high-frequency levels of the histogram occupy an excessively large range of the output image's dynamic range.

B. Stratified Parametric-Oriented Histogram Equalization (SPOHE)

SPOHE is an advanced image enhancement approach that extends traditional global histogram equalization with local statistical modeling combined with stratified sampling. In contrast to traditional methods, which have the potentials for mean-brightness shifts, over-enhancement of densely populated regions, and loss of detail in low-density areas, SPOHE adapts the modulation of the enhancement based on the local distributions of intensity. The approach ensures that both subtle and prominent features within an image are preserved and enhanced appropriately.

For a support region of size, the population of pixels is partitioned into $M\times N$ mutually exclusive strata B_k. Each of these layers is composed of pixels with similar features of intensity.

This allows for the fine-tuning of contrast. The overall number of pixels in the region is given by the expression:

$$G=\sum_{k=1}^{K}|B_k| \qquad (2)$$

This equation shows the idea that the total number of pixels is the sum of the individual pixel groupings. Stratification is a key feature of SPOHE, which enables it to work with images having non-uniform histograms or textures.

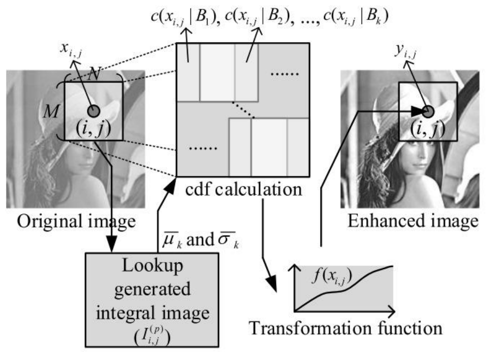


Fig. 1. Flowchart of the SPOHE for one pixel (xi,j) enhancement.

The total number of strata K is determined by the stratification parameters α and β as:

$$K=(\beta-\alpha+1)^2, \quad (\alpha<\beta,\ \beta<M,N) \tag{3}$$

Optimal values of α and β balances the granularity of enhancement with computational complexity. With smaller strata, finer details are captured along with the preservation of local contrast, whereas larger magnitude strata reduce computation but can smooth minor features. One of the commonly used pairs involves $(\alpha,\beta)=(1,7)$, which is generally adopted as a good balance between enhancement quality and processing speed.

Within each stratum, the distribution of pixel intensities is modeled as a Gaussian distribution. The mean μ_k and standard deviation σ_k of the k-th stratum are computed as:

$$\mu_k=m^{(1)}_{i,j}, \tag{4}$$

$$\sigma_k=\sqrt{m^{(2)}_{i,j}-(\mu_k)^2} \tag{5}$$

Here, the mean characterizes the central tendency in pixel values-the common intensity in a stratum-whereas the standard deviation is a measure of dispersion in intensities that captures the variation in intra-stratum contrast. These two statistics provide the basis for adaptive enhancement.

For each pixel $x_{i,j}$ in stratum B_k, the Gaussian-based cumulative distribution function (CDF) is defined as:

$$c(x_{i,j}|\mu_k,\sigma_k)=\frac{1}{2}\left[1+\operatorname{erf}\left(\frac{x_{i,j}-\mu_k}{\sqrt{2}\,\sigma_k}\right)\right] \tag{6}$$

CDF translates the given pixel intensity to a probability value with respect to the local distribution. This translation ensures that pixels having similar local statistics are enhanced consistently so as to preserve their natural texture and gradient appearances.

The final grayscale distribution in the support area is obtained by integrating the CDFs of all K strata:

$$c(x_{i,j}|B_{i,j})=\sum_{k=1}^{K} c\,(x_{i,j}|\mu_k,\sigma_k) \tag{7}$$

SPOHE uses all the layers' input values(strata), including local and regional variations in intensity. This prevents any single high-frequency region from dominating the process and keeps the contrast enhancement consistent throughout the image.

The transformation function stretches the estimated CDF to the full range, e.g., 0-255:

$$f(x_{i,j})=L\cdot c(x_{i,j}|B_{i,j}) \tag{8}$$

Scaling normalizes the normalized CDF to the actual range of image intensities. This increases the contrast by stretching the image while preserving the relative differences between the pixels.

The improved output pixel value is calculated as:

$$y_{i,j}=f(x_{i,j}) \tag{9}$$

To efficiently obtain the statistical moments for each stratum, SPOHE employs the integral image.. The generalized integral image $I^{(p)}_{i,j}$ (for p=1,2) is defined as:

$$I^{(p)}_{i,j}=\sum_{m=0}^{i}\sum_{n=0}^{j} x^p_{m,n}=x^p_{i,j}+I^{(p)}_{i-1,j}+I^{(p)}_{i,j-1}-I^{(p)}_{i-1,j-1} \tag{10}$$

The p-th moment $m^{(p)}_{i,j}$ for any stratum B_k is calculated in constant time using four lookups:

$$m^{(p)}_{i,j}=\frac{1}{|B_k|}\Big(I^{(p)}_{i+\lfloor M/2\rfloor,j+\lfloor N/2\rfloor}-I^{(p)}_{i+\lfloor M/2\rfloor,j-\lceil N/2\rceil} -I^{(p)}_{i-\lceil M/2\rceil,j+\lfloor N/2\rfloor}+I^{(p)}_{i-\lceil M/2\rceil,j-\lceil N/2\rceil}\Big) \tag{11}$$

The use of integral images makes this process computationally efficient, such that both mean and standard deviations can be computed in constant time irrespective of the size of a stratum. This level of efficiency enables SPOHE to be used on high-resolution images.

Overall, SPOHE provides a contrast enhancement process that is adaptive and locally aware, preserving details in images, ensuring that there is no shift in brightness, and eliminating many artifacts associated with global histogram-based methods. The combination of adaptability and efficiency makes SPOHE suitable for applications in medical images, remote-sensing images, and natural scene images. The combination of stratified sampling, Gaussian modeling, and efficient integral computation enables SPOHE to produce high-quality and aesthetically pleasing image enhancements suitable for both research and practical applications.

The main drawback in SPOHE is its fixed parameterization used in the process of stratification. The fixed number and sizes of strata determine the level of detail in the images. Unless these parameters are well-tuned to the images, there is a possibility of over-smoothing small details in images using large strata or increased computation and amplification of noise in images using small strata. As a result, SPOHE might not adapt optimally to local intensity distributions in images, as these might be quite diverse from one image to another.

III. ADAPTIVE STRATA SELECTION IN PARAMETRIC HISTOGRAM EQUALIZATION (ASPHE)

ASPHE extends the conventional SPOHE framework by incorporating an adaptive parameter selection mechanism. Unlike SPOHE, which relies on manually fixed stratification parameters, the number of strata in ASPHE is determined dynamically based on the local statistical complexity of the image. In the current implementation, the support region used for feature computation is the whole image; hence, the global complexity of the image was used for determining the parameter. This setting provides a simple adaptive enhancement without processing the image in regions. Therefore, it reduces the computational load but yields an enhanced contrast and detail preservation compared to fixed-parameter SPOHE. Possible future extensions will be to determine the parameter in the tile or block levels in order to achieve more localized adaptation and finer stratification in regions with variable textures or edge densities.

A. Motivation

In SPOHE, the two stratification parameters define the number and size of strata in a support region. Although one is set to unity to maintain symmetric processing, the other governs the granularity of enhancement. Fixed values serve certain images satisfactorily; they often lead to suboptimal performance in diverse imaging contexts. Natural, medical, and low-light images tend to have significantly varying local properties. Fine partitions are preferred in regions with highly complex textures in order not to suppress subtle intensity variations. The converse holds for smoother regions, such as clear skies or uniform backgrounds, where coarser partitions avoid excessive enhancement and save computational cost. To address these challenges, ASPHE proposes a content-driven adaptive stratification scheme where the relevant parameter will be automatically computed for the image in terms of an overall complexity score, while the other remains at unity. Currently, this computation is global; the framework will allow further refinements to block or tile level adaptive stratification in images that exhibit spatially heterogeneous content.

© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1714865

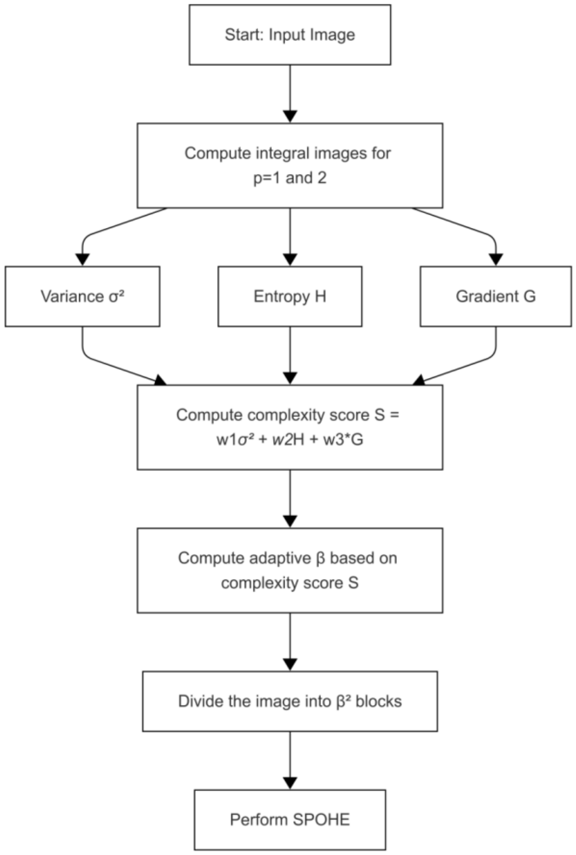


Fig. 2. Flowchart of the Proposed ASPHE for βselection.

B. Local Feature Extraction

ASPHE extracts three complementary statistical features from the support region to characterize image complexity: variance, entropy, and mean gradient. These features capture distinct aspects of image content and directly influence the adaptive selection of β.

i.Local Variance(σ^2)

The local variance σ^2 reflects the spread of gray levels within the support region. Using integral images of I and I^2, variance is computed as:

$$\sigma^2=m^{(2)}-\mu^2,$$
$$\mu=\frac{1}{|R|}\sum_{(u,v)\in R} I(u,v),$$
$$m^{(2)}=\frac{1}{|R|}\sum_{(u,v)\in R} I(u,v)^2$$

The normalized variance is

$$\hat{\sigma}^2=\frac{\sigma^2}{V_{\text{ref}}}, \tag{12}$$

with $V_{\text{ref}}\approx 127.5^2$ for 8-bit images or set to the 95th percentile of regional variances for robustness. Variance indicates contrast diversity. Low variance (nearly uniform regions) leads to small β, avoiding unnecessary enhancement and noise amplification. High variance regions with strong contrast or multiple intensity modes require fine stratification, so ASPHE maps them to larger β values.

ii.Entropy(H)

Entropy measures histogram complexity and multimodality:

$$H=-\sum_{g=0}^{B-1} p_g \log_2\left(p_g+\epsilon\right), \quad p_g=\frac{n_g}{|R|} \tag{13}$$

Normalized entropy is

$$\hat{H}=\frac{H}{\log_2 B} \tag{14}$$

with $B=16$ and $\epsilon=10^{-9}$. Low entropy indicates unimodal distributions where fine stratification is unnecessary. High entropy reflects multimodal intensity distributions, where a larger β captures diverse local modes accurately.

iii.Gradient(G)

The mean gradient quantifies structural information using Sobel operators:

$$K_x=\begin{bmatrix}-1 & 0 & +1\\ -2 & 0 & +2\\ -1 & 0 & +1\end{bmatrix}, \quad K_y=\begin{bmatrix}-1 & -2 & -1\\ 0 & 0 & 0\\ +1 & +2 & +1\end{bmatrix},$$
$$G_x=I*K_x, \quad G_y=I*K_y,$$
$$G=\sqrt{G_x^2+G_y^2}$$

The regional mean gradient is

$$\bar{G}=\frac{1}{|R|}\sum_{(u,v)\in R} G(u,v) \tag{15}$$

normalized as

$$\hat{G}=\frac{\bar{G}}{G_{\text{ref}}} \tag{16}$$

with $G_{\text{ref}}\approx 1442$. Low gradients indicate flat regions, mapped to small β, while high gradients correspond to edges or structural details, mapped to larger β to preserve boundaries and avoid haloing. Gaussian pre-smoothing (σ=0.5 – 1.0) may reduce noise before computing gradients. All three factors, variance, entropy, and gradient, work together to provide a comprehensive view of the complexity of the image. Their importance may be adjusted using weights w_1, w_2, w_3 to reflect the features that are most important to the application at hand. For instance, the importance of variance may be increased in medical images where contrast is significant, entropy in scenes where texture is prominent, and the gradient in images where edges are important.

C. Complexity Score and Adaptive Stratification

The normalized features are combined into a complexity score:

$$S = w_1 \hat{\sigma}^2 + w_2 \hat{H} + w_3 \hat{G}, \quad w_1 + w_2 + w_3 = 1 \tag{17}$$

The stratification parameter β is then obtained as:

$$\beta = \text{odd\_ceil}\left(\beta_{\min} + \left(\beta_{\max} - \beta_{\min}\right) S^{\gamma}\right) \tag{18}$$

where $\beta_{\min} = 3$ sets the coarsest granularity, $\beta_{\max} = 15–21$ caps the finest stratification based on support size, and γ adjusts sensitivity. Linear scaling ($\gamma = 1$) maps complexity proportionally to stratification, $\gamma > 1$ favors conservative partitioning, and $\gamma < 1$ increases sensitivity to small variations in S. The odd-ceiling ensures symmetric region division for consistent Gaussian approximation.

Smooth regions with low variance, entropy, and gradient produce low complexity scores and are assigned β close to $\beta_{\min}$, avoiding noise amplification. Highly textured regions with high variance or entropy reach β near $\beta_{\max}$ for fine modeling of multimodal histograms. Edge-dominated regions see a local increase in β even if variance or entropy is moderate, preserving structural details and preventing halo artifacts. The adjustable weights w_1, w_2, w_3 allow the user to prioritize features according to the imaging context, making ASPHE highly flexible and robust for diverse applications. Currently, the support region is the entire image, so β is selected globally. In future work, ASPHE may be extended to tile-level or block-level parameter selection, enabling more localized adaptive enhancement for images with spatially varying textures, contrast, or edge distributions.

D. Implementation

This section summarizes the ASPHE theory and operations in a way that can be practically implemented.

Algorithm 1: Adaptive Stratified Parametric-Oriented Histogram Equalization

Step 1: Input a grayscale or color image.

Step 2: Compute the integral images $I_{i,j}^{(p)}$ for $p = 1,2$ to facilitate fast computation of local statistical features.

Step 3: Extract local features in parallel to characterize image complexity. Compute the variance σ^2 to measure local intensity dispersion, the entropy H to capture information content or texture, and the gradient G to evaluate edge and structural information within the image.

Step 4: Compute the complexity score S as a weighted combination of the extracted features:

$$S = w_1 \sigma^2 + w_2 H + w_3 G$$

where w_1, w_2, w_3 are empirically determined weights for each feature.

Step 5: Determine the adaptive parameter β based on the complexity score:

$$\beta = \text{odd\_ceil}\left(\beta_{\min} + \left(\beta_{\max} - \beta_{\min}\right) S^{\gamma}\right)$$

where $\beta_{\min}$ and $\beta_{\max}$ define the allowable range of block divisions, and γ controls the sensitivity of adaptation to the complexity score.

Step 6: Divide the input image into β^2 non-overlapping blocks and form strata B_k for local processing.

Step 7: Perform SPOHE on the image by applying local histogram equalization within each stratum to adaptively enhance the contrast.

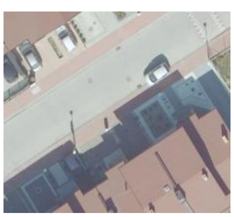
Step 8: Stop.

IV. EXPERIMENTAL RESULTS

While performing a holistic evaluation of techniques for image enhancement, subjective visual perception and quantitative objective measures have to be taken into consideration. In subjective evaluation, visual observation of enhanced images is done to verify whether the enhanced contrast, detail, and overall appearance are as per human perception. However, since subjective assessment is affected by perception, it may vary from one observer to another. For this reason, objective metrics are highly required because they provide consistent and reproducible evaluation.

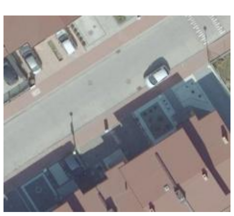
The discrete entropy (H), the Average Mean Brightness Error (AMBE), and the Contrast Improvement Index (CII) are used as objective metrics for the proposed ASPHE method. Discrete entropy measures the quantity of information from an image. A higher value indicates that the image is rich in detail, with a good preservation of essential features. AMBE calculates the difference between the mean brightness of the original and enhanced images and gives the measure about the ability of the method to preserve natural brightness. CII measures the improvement in contrast due to enhancement. By combining subjective assessment with such an objective measure, the performance of ASPHE can be fully assessed. Experimental results on a diverse set of standard test images demonstrate the capability of the proposed method in enhancing image contrast without distorting crucial image details and brightness.

A. Subjective Assessment



(a)

(d)



(b)

(e)

(c)

Figure 3: Results for image house: Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).

It can be seen from Figure 3, which depicts the house image. The original aerial image has less contrast, making it difficult to see the house. Although the RSWHE method improves the image to a certain degree, the dark areas are still under-enhanced. On the other hand, the DHE and SPOHE methods have greatly improved the contrast but have also made the dark areas too dark, making the image look unnatural. However, the ASPHE method provides a better balance in making the image look natural.

(a)

(d)

(b)

(e)

(c)

Figure 4: Results for image desert: Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).

A comparison of the desert scene in Figure 4 and the city scene in Figure 5 reveals that both scenes are suffering from the effects of haze and dim lighting. While the desert scene benefits from the application of DHE and SPOHE in terms of contrast, it suffers the drawback of losing the details of the shadows. On the other hand, the application of ASPHE maintains the clarity of the sandy areas and the residential areas. Similarly, for the city scene, all three methods have been effective in removing the haze. However, the application of DHE and SPOHE has enhanced the image to an extreme level, suggesting an artificial lighting condition. ASPHE has been more effective in removing the haze while maintaining the natural tones and textures of the image, creating an appealing image with no distortions.

(a)

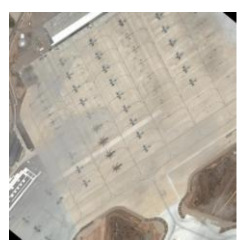
(d)

(b)

(e)

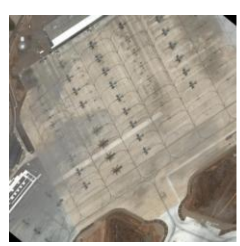
(c)

Figure 5: Results for image city: Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).



(a)

(d)



(b)

(e)

© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1714865

(c)

Figure 6: Results for image flights:Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).

A better example can be seen in Figure 6 (flights image), where the faded airfield requires a heavy touch of contrast adjustment. SPOHE provides excellent contrast but at the expense of much higher noise and artifacts, which affects the overall image quality. On the other hand, ASPHE helps to clarify the runway and the area around it while controlling the noise level, making it a cleaner and sharper image. This difference in performance reflects the advantages of ASPHE when you need to enhance the image but also require finer details to be maintained despite the heavy touch of enhancement.

(a)

(d)

(b)

(e)

(c)

Figure 7: Results for image flowers:Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).

(a)

(d)

(b)

(e)

(c)

Figure 8: Results for image white roses: Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).

Algorithmic differences become more pronounced in the case of natural scenes, such as the flower image of Figure 7 and the whiteroses image of Figure 8. On the flower image, sharper contrast favorably affects DHE and SPOHE but both methods result in excessively intense dark regions. Besides enhancing contrast, ASPHE enhances the subtle textures in petals, yielding a more natural and pleasing result. Similarly, in the white roses image, both DHE and SPOHE lighten the petals and give a grainy appearance, while ASPHE preserves clarity and subtle detail-a well-enhanced image should not lose smoothness.

Figure 9: Results for lena image : Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).

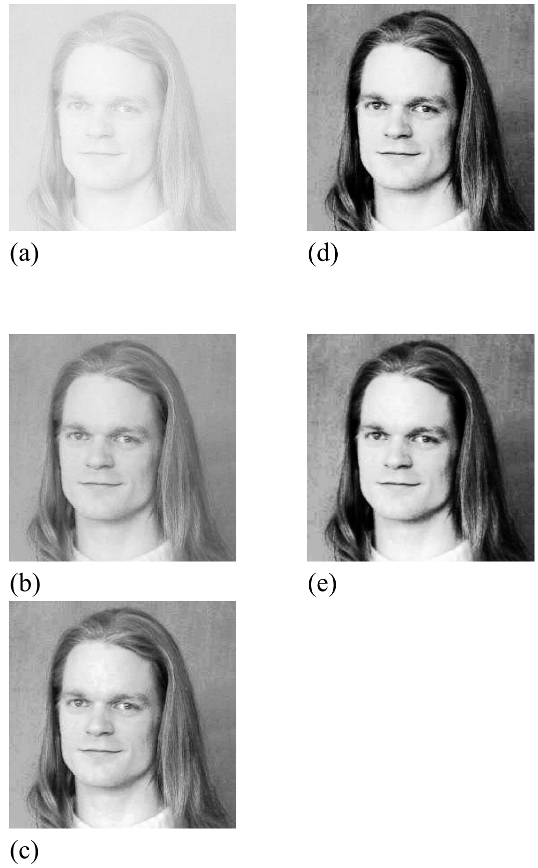


Figure 10: Results for image man :Panel (a) is the original image. The enhancement made by the RSWHE algorithm is in panel (b). The image enhanced by DHE is in panel (c). Panel (d) shows the image enhanced by SPOHE. The image enhanced using the proposed ASPHE method is in panel (e).

Finally, distinctions between color and grayscale enhancement become apparent in Figure 9 (Lena image) and Figure 10 (man image). The Lena image already has moderate contrast; thus, aggressive methods like DHE and SPOHE over-saturate the image-especially in the red channel-resulting in an unnatural skin tone. On the other hand, ASPHE enhances contrast judiciously while preserving color balance, yielding the most natural rendition. The man's image is more challenging since it has a very low original contrast. All algorithms recover facial features, but DHE and SPOHE enhance background noise, reducing clarity. ASPHE uncovers features in the face and hair with reduced noise, hence recovering features of even severely degraded images quite effectively.

B. Objective Assessment

Objective assessment gives the quantitative appraisal of techniques of image enhancement, thereby providing reproducible performance measures that complement subjective visual analysis. The metrics usually employed in this work are Entropy (H), Absolute Mean Brightness Error (AMBE), and Contrast Improvement Index (CII).

TABLE 1 ENTROPY COMPARISON OF VARIOUS HISTOGRAM EQUALIZATION METHODS.

Image	Original	DHE	RSWHE	SPOHE	ASPHE
House	0.83	0.94	0.85	0.91	0.95
Desert	0.84	0.84	0.84	0.84	0.99
City	0.81	0.81	0.81	0.81	0.98
Flights	0.82	0.80	0.81	0.79	0.98
Flowers	0.86	0.97	0.94	0.98	0.99
Whiteroses	0.89	0.97	0.93	0.96	0.98
Lena	0.96	0.97	0.97	0.95	0.96
Man	0.71	0.93	0.88	0.94	0.98

Entropy is a measure of the amount of information or detail present in an image and hence closely related to contrast enhancement; the higher the entropy, the better the distribution of gray levels in general and, hence, the visibility of image features. The proposed ASPHE method outperforms DHE, RSWHE, and SPOHE in terms of entropy for almost all test images from Table 1. The conventional methods improve entropy only by few percents compared to the original input images, while ASPHE always reaches the maximum values, reflecting in a good enhancement of image details and contrast. Images with low original entropy, such as "Man," have the largest increase, with entropy rising from 0.71 to 0.98, while images characterized by high entropy, such as "Lena," are well-preserved and not over-enhanced.

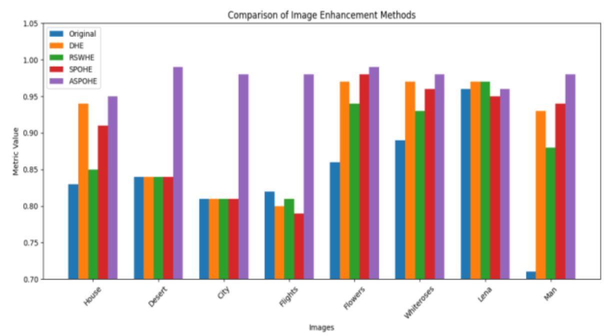


Figure 11: Grouped Bar Graph depicting Entropy comparisons for the ASPHE with other methods.

Figure 11 shows grouped bar graphs for these entropy comparisons visually and further underlines the effectiveness of ASPHE. These quantitative results confirm that ASPHE not only ensures maximum information content but also preserves naturalness of the visual appearance and provides more truthful and balanced enhancement than other histogram-equalization methods.

AMBE is a basic measure of image enhancement, which determines the difference in average brightness between the original and enhanced image. In other words, it measures the fidelity of brightness: the lower the AMBE, the more the process of enhancement has preserved the natural and realistic illumination of the scene.

From this scatter plot, Figure 12, it might be inferred that the methods adopt different strategies in the balance between enhancement and brightness preservation.

© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1714865

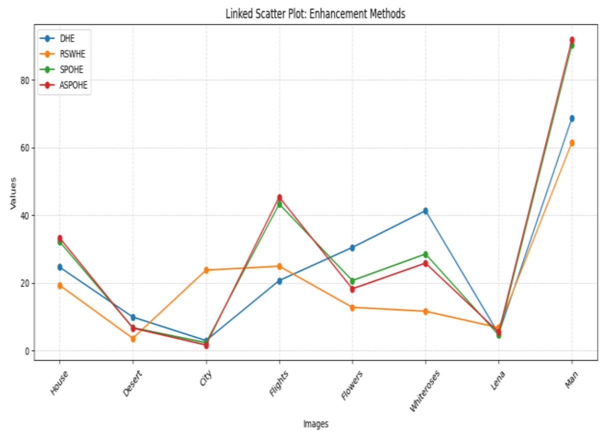


Figure 12: Linked Scatter plot for the AMBE for ASPHE with the other methods.

The DHE and RSWHE methods consistently occupy the lower region of the graph, reflecting superior performance by inducing minimal changes in mean brightness. The proposed ASPHE method and SPOHE trace the upper trajectory across most images, with pronounced spikes for images such as "Flights" and "Man."

This pattern shows that a main weakness of ASPHE and SPOHE is poor brightness preservation, as reflected by their high AMBE values and resultant large and highly variable shifts in overall luminance. This weakness can be interpreted positively: the large mean-brightness shift reflects their aggressive, non-conservative contrast-enhancement mechanism. While brightness fidelity is sacrificed-high AMBE-such an approach is often necessary to achieve maximum contrast and reveal the most detail, a claim corroborated by the reference text and consistent with the goal of attaining maximal visual detail rather than strict naturalness.

TABLE 2
CONTRAST IMPROVEMENT INDEX (CII) COMPARISON.

Image	DHE	RSWHE	SPOHE	ASPHE
House	1.4831	1.0083	1.8603	1.7929
Desert	2.1655	0.9740	2.5145	2.4738
City	1.9825	1.1892	3.1324	3.0377
Flights	1.9899	1.4256	2.7823	2.9325
Flowers	1.7356	1.4291	2.2652	2.2432
Whiteroses	1.5183	1.1974	1.8659	1.8096
Lena	1.1066	1.1066	1.2824	1.2663
Man	3.6431	2.7711	5.1613	5.1549

The CII is a quantitative measure used to determine the amount of improvement achieved by different algorithms with respect to an original image. This is evaluated as the ratio between enhanced image contrast and original image contrast, whereby larger CII values correspond to higher improvement in contrast. Hence, CII is used as a reliable metric to assess the quality of various approaches aimed at enhancement in terms of the visibility and information preservation capability.

Moreover, the CII can be useful in the analysis of how the enhancement algorithms respond to changes in illumination and texture distribution. Because it reflects relative contrast change rather than absolute intensity variation, it helps to identify those methods that improve local and global contrast without excessive amplification or visual distortion. This makes the CII a good indicator for comparing enhancement techniques regarding their robustness under different conditions.

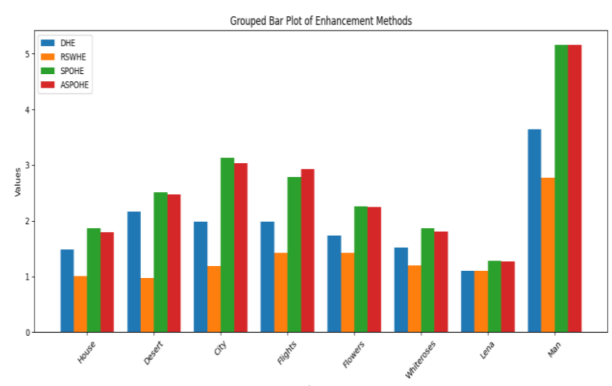


Figure 13: Grouped Bar Graph depicting CII comparisons for the ASPHE with other methods.

Table 2 and Figure 13 depict the CII values calculated using DHE, RSWHE, SPOHE, and the proposed ASPHE techniques for a sequence of images. The observations made from the results show that ASPHE yields a consistently high CII value, often slightly behind SPOHE but with better stability over different categories of images. Indeed, SPOHE has higher values over the complex images City, Flights, and Man than ASPHE, which tends to preserve almost the same value without facing the risk of over-enhancement. On the natural images Flowers and Whiteroses, ASPHE gives equal improvement without excessive amplification, proving its adaptability. Overall, the results prove that ASPHE produces competitive or superior CII values on the tested images, therefore confirming its robustness as an enhancement technique.

In all three parameters, ASPHE excels. Entropy proves that it preserves the finest details in an image. The high scores in AMBE parameters signify a lack of brightness fidelity, but this is a trade-off against better detail extraction. The CII parameters prove that ASPHE provides competitive contrast enhancements, sometimes matching or beating SPOHE without over-boosting. To sum up, ASPHE provides a healthier balance in detail, contrast, and visibility compared to conventional methods, but at a cost to brightness fidelity.

V. CONCLUSION

In essence, the Adaptive Strata Selection in Parametric Histogram Equalization (ASPHE) takes the field of contrast enhancement a step further by addressing the major limitation in SPOHE: the fixed stratification parameters. With adaptive parameters based on variance, entropy, and gradient statistics, ASPHE adjusts the degree of enhancement based on the image content. This provides a better balance for areas with high image complexity and areas where the image is smoother.

Clearly, ASPHE excels when compared to SPOHE in both subjective and objective evaluations. It provides high-quality images with maximum detail visibility in the entire frame. The results are free from artifacts and have a natural look. The entropy analysis also proves that ASPHE provides better results by retaining more image information. The results also show high contrast enhancement capability for various types of images by analyzing the CII metrics. Although ASPHE results in a higher AMBE value than SPOHE, indicating less brightness fidelity, this trade-off is justified to ensure that subtle features are visible in areas where other methods would fail to detect them.

The flexibility and robustness of this method ensure that ASPHE finds a wide range of applications from natural image enhancement to medical imaging and visual surveillance. Future directions for this method could be to use block stratification to adjust the parameters locally for better results. Alternatively, the use of feature weighting or hybrid deep learning could be incorporated for specific optimization requirements.

In conclusion, ASPHE provides robust and effective contrast enhancement results by overcoming the limitations in SPOHE while leaving plenty of room for future research.

REFERENCES

[1] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 3rd ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2008.

[2] M. Abdullah-Al-Wadud, Md. Hasanul Kabir, M. Ali Akber Dewan, and O. Chae, "A Dynamic Histogram Equalization for Image Contrast Enhancement,"*IEEE Transactions on Consumer Electronics*, vol. 53, no. 2, pp. 593-600, May 2007.

[3] M. Kim and M. G. Chung, "Recursively Separated and Weighted Histogram Equalization for Brightness Preservation and Contrast Enhancement,"*IEEE Transactions on Consumer Electronics*, vol. 54, no. 3, pp. 1389-1397, Aug. 2008.

[4] S. M. Pizer, E. P. Amburn, J. D. Austin, R. Cromartie, A. Geselowitz, T. Greer, B. ter Haar Romeny, J. B. Zimmerman, and K. Zuiderveld, "Adaptive Histogram Equalization and Its Variations,"*Computer Vision, Graphics, and Image Processing*, vol. 39, no. 3, pp. 355-368, Sept. 1987.

[5] Y.-T. Kim, "Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization,"*IEEE Transactions on Consumer Electronics*, vol. 43, no. 1, pp. 1-8, Feb. 1997.

[6] Y. Wan, Q. Chen, and B.-M. Zhang, "Image Enhancement Based on Equal Area Dualistic Sub-Image Histogram Equalization Method,"*IEEE Transactions on Consumer Electronics*, vol. 45, no. 1, pp. 68-75, Feb. 1999.

[7] S.-D. Chen and A. R. Ramli, "Minimum Mean Brightness Error Bi-Histogram Equalization in Contrast Enhancement,"*IEEE Transactions on Consumer Electronics*, vol. 49, no. 4, pp. 1310-1319, Nov. 2003.

[8] S.-D. Chen and A. R. Ramli, "Contrast Enhancement Using Recursive Mean-Separate Histogram Equalization for Scalable Brightness Preservation,"*IEEE Transactions on Consumer Electronics*, vol. 49, no. 4, pp. 1301-1309, Nov. 2003.

[9] P. Soille, *Morphological Image Analysis: Principles and Applications*, 2nd ed. Berlin, Germany: Springer-Verlag, 2003.

[10] A. Srikrishna, M. Pompapathi, and G. Srinivasa Rao, "Parametric Based Morphological Transformation for Contrast Enhancement of Color Images in Poor-Lighting,"*Sādhanā*, vol. 40, no. 2, pp. 395-410, Apr. 2015.

[11] Y.-F. Liu, J.-M. Guo, B.-S. Lai, and J.-D. Lee, "High Efficient Contrast Enhancement Using Parametric Approximation," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Vancouver, BC, Canada, May 2013, pp. 2444-2448.

[12] Y.-F. Liu, J.-M. Guo, and J.-C. Yu, "Contrast Enhancement Using Stratified Parametric-Oriented Histogram Equalization,"*IEEE Transactions on Circuits and Systems for Video Technology*, vol. 27, no. 6, pp. 1171-1181, June 2017.