Advancing Image Illumination Through Intrinsic Transfer

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Abstract. Intrinsic picture modification has become a vital method in the rapidly developing fields of computer vision and image processing, helping to improve the usability and interpretability of the digital images. For correcting the photo realistic-losses present in the image there are many algorithms such as NLM(Non-Local Means), Histogram, Dark channel prior, Retinex Algorithm. These algorithms couldn't identify the boundary of the images. Comparing with the algorithms present in the literature, Gamma Algorithm shows better results in terms of PSNR and SSMI. To improve the PSNR and SSMI, a combination of Gamma and IIT(Intrinsic Image Transfer) has been proposed. Initially this algorithm identifies the hazy effects present in the image using K-Means Clustering, Guided Filter and Gamma Correction. The illumination manipulation model is used to determine the other corresponding factors, such as blurred appearance and darkness of the image, by applying a locally linear embedding (LLE) algorithm that is designed to identify illumination-invariant reflectance, after the haze present in the image has been identified by segmenting the sky region. LLE provides an alternative optimization method. A closed-form solution for controlling image illumination is implemented, leveraging an exemplar image. Additionally to calculate the Qualitative measures for this model PSNR and SSMI are used.

Keywords: Image Segmentation, Gamma Correction, Guided Filter, Image Illumination, Image Reflectance, Image Content, Intrinsic Image Transfer, Illumination Manipulation

1. Introduction

One of the most important issues in the ever-changing field of image processing is efficiently controlling lighting to reduce photorealistic losses in visual data. The investigation of perception problems in conjunction with picture illumination has its origins in Helmholtz's work. He put up a significant theory on human vision, arguing that regardless of the lighting, we always perceive a scene's "intrinsic" properties. This idea, which is sometimes called "lightness constancy [1]" suggests that our perception of an object's key characteristics doesn't change when the lighting does. Helmholtz's groundbreaking analysis laid the foundation for understanding how people see and process visual information, regardless of variations in ambient lighting.

The human visual system (HVS) and human perception of illumination are complex and not fully understood, with recent studies highlighting the intricate mechanisms, interactions, and feedback involved[1]. The lightness and whiteness of a scene, as perceived by humans, remain a mystery despite decades of research. The HVS and illumination perception are closely related, with poorly understood processes and interactions that make it challenging to solve the puzzles surrounding human vision[2][3].

A number of applications, including as HDR compression, picture tone mapping, enhancement, and illumination correction, address the common challenge of correcting illumination conditions to reveal more visual information. In order to minimize the deterioration of brightness, contrast, color, and saturation, computational models have been developed to optimize illumination for balanced distributions. Retinex-based techniques and tone mapping operators (TMO)[4][5] comprise the two primary groups of these attempts. Similar to gamut mappings, TMO offers simplicity at the expense of potential visual distortions. It does this by using certain tone-mapping operators or curves to correct color intensities. Conversely, Retinex-based[6][7] techniques break down images into intrinsic layers, allowing for more believable outcomes, albeit they have difficulties with intrinsic image decomposition because of under-constraints and inadequate prior knowledge.

Specifically, photographs with blurry edges provide a major challenge that requires strong solutions to improve image quality [15]. In response, the Intrinsic Image Transfer (IIT) method is presented as a novel solution thoroughly developed for overcoming the complicated issues surrounding lighting modifications [16].

The following contributions from the IIT technique change picture lighting manipulation[16]:
1. Generalized Minimization Framework: It presents a unique framework that uses three photorealistic losses: light, reflectance, and content which characterize the "intrinsic" layers of the image.
2. Filtering Operator and Locally Linear Embedding (LLE) Algorithm: It presents a basic filtering operator to imitate spatial smoothing in image lighting, as well as LLE for illumination-invariant reflectance determination.
3. Closed-Form Solution for Lighting Regulation: Applying a closed-form solution using a "exemplar image" outperforms state-of-the-art techniques on actual photo challenges in terms of both qualitative and quantitative outcomes.
The incorporation of the gamma model, a crucial element that facilitates the comprehension and adjustment of brightness levels in a picture, is the basis of the IIT algorithm. The nonlinear connection between pixel intensity levels and perceived brightness is crucially represented by the gamma model[15]. By utilizing this model, the IIT algorithm reaches an advanced degree of adaptability.
Moreover, every image has a precise point that causes it to appear dull or blurry, and this point can be identified through the three-step gamma correction procedure:
1. Sky Region Segmentation: It uses K-Means technique, to split the image into two clusters- sky region and non-sky region.

2. Guided Filter: It is used to refine the sky region.
3. Gamma Correction: It is used to enhance visual quality.

2. LITERATURE SURVEY

"**Ji-Hee Han *etal..* [8]"** A novel 3-D color histogram equalization technique is presented to overcome constraints in the RGB intensities using cumulative distribution function (CDF). It attempts to produce a uniform probability density function (pdf) in the intensity domain by defining a CDF with an iso-luminance-plane boundary. This technique, which is similar to grayscale histogram equalization, effectively increases brightness contrast. On the other hand, if there are noise, artifacts, or distortions in the image, its performance might be reduced.

"Ramanathan Vignesh *etal..* [9]" In order to speed up the process, the research provides a Fast Non-Local Means (NLM) Computation approach employing Probabilistic Early Termination (PET). PET removes blocks that are not identical by considering the likelihood of distortion values. It performs better than benchmark systems in terms of visual perception improvement, PSNR quality improvement, and complexity reduction.

"Tae Ho Kil *etal..* [10]" The study presents a single picture dehazing technique that incorporates a "reliability map" to reduce depth estimate mistakes, improving upon the dark channel prior. This map evaluates the consistency of obtaining a transmission factor per pixel, which is important in situations where objects and haze have similar colors. Experimental results show less color distortion and better transmission maps.

"Yu-Xiong *etal..* [11]" Patches on high-confidence structures are given priority for filling order using Weighted Sparse Non-Negative Matrix Factorization (WSNMF), which sequentially propagates patches inward from the border. By looking for comparable patches in the source region, the algorithm creates a data matrix. It then utilizes NMF for matrix completeness, modifying weights in accordance with patch similarity.

"S. Yousefi1 *etal..* [12]" In this research, a statistical modeling strategy for binary second harmonic generation (SHG) images of cervical tissue is presented utilizing Markov Random Field (MRF). MRF uses energy functions and probability conditions to capture pixel interactions; parameters are determined using the least squares technique. Although MRF offers a statistically sound framework for pixel-interaction representation. The discrete label set might not adequately represent the complex and continuous properties that are present in biological tissues in the real world.

Jui-Ying Lu *etal..* [13]" The technique uses a Convolutional Neural Network (CNN) in place of the conventional Delay-and-Sum (DAS) beamforming and IQ demodulation processes for beamforming in ultrasonic imaging. Training consists of transfer learning on multiple-angle PW phantom images after pretraining on simulated and single-angle PW phantom images. Improved primary feature capture is seen in the resulting B-mode ultrasound images, which may indicate a breakthrough in PW imaging techniques.

"Li Shen *etal..* [14]" The approach incorporates both local and global sparsity restrictions to establish a sparse representation of reflectance in natural photos. The global sparsity requirement is enforced when multiresolution analysis is conducted using red-black wavelets. The algorithm offers a practical method for intrinsic picture decomposition by taking into account chromaticity configurations at various scales and reducing the cost function.

"Sumit Kr.Yadav *etal..* [15]" The suggested technique offers a simple and efficient way to dehaze a single image by using the gamma algorithm. The gamma correction method expands the applicability of the Dark Channel Prior (DCP) method to broader sky regions, yet it still performs exceptionally well in dehazing small sky regions. Gamma correction improves contrast in images, which helps distinguish details in areas of light and dark.

"Junqing Huang *etal..* [16]" To separate intrinsic image components, Junqing Huang devised the Intrinsic Image Transfer (IIT) technique, which combines filter identification, LLE weight computation, and reconstruction phases. It provides a thorough method for modifying illumination in computer graphics, resulting in renderings that are more lifelike and give you more control over lighting effects and materials.

Prior research that sought to determine illumination, reflectance, and content used the IIT method, which applies Retinex theory to identify the factors influencing picture illumination, reflectance, and content. Many algorithms can be used in place of the Retinex Model. For example, the Histogram Equalization algorithm [8] converts images to grayscale; the Non-Local Means (NLM) algorithm [9] is based on Probabilistic Early Termination (PET) which focuses on pixel neighborhood distortion calculation used to achieve early termination based on distortion value; the Dark Channel algorithm [10] is used to estimate the correct transmission map regardless of object color using reliable pixels only (linear fitting is used for unreliable pixels) and when compared to other algorithms that employ a way to identify the edge of the images, Gamma Algorithm[15], which primarily focuses on haze impact, this algorithm uses a very simple and effective strategy for haze removal.

3. EXISTING METHOD:

Previous work used an Intrinsic Image Transfer (IIT) method for adjusting image lighting inside an optimization framework which incorporates photo-realistic losses of lighting, reflectance, and content using previous knowledge of spatially-varying light-invariant reflectance. Unlike previous breakthroughs that emphasize intrinsic picture decomposition, which directly defines losses on images and produces high-quality results across illumination-related tasks.

An intrinsic picture model that separates an image's reflectance (R) and lighting (L). Each of these components plays a distinct role in controlling an image's color, brightness, and contrast. An Intrinsic Image Transfer (IIT) approach for manipulating image lighting within an optimization framework[16]. Using prior knowledge of spatially-varying light-invariant reflectance, it integrates photo-realistic losses of illumination, reflectance, and content. This model provides high-quality outcomes across illumination-related tasks by directly defining losses on images, in contrast to prior advances that emphasize intrinsic image decomposition. Its extensive processing time, which is caused by large-scale PCG (preconditioned conjugate gradients) solver processes and LLE (locally linear embedding) weights, can be reduced in the future by employing an effective subsampling method. An Intrinsic Image model that divides images into components for lighting (L) and reflectance (R). These elements each have a unique function in regulating the brightness, contrast, and color of an image. Explicit intrinsic picture decomposition is still difficult to achieve, even with previous attempts, especially in complex lighting and material conditions.

The field of illumination control has consistently encountered obstacles pertaining to photorealistic losses. The IIT algorithm uses three photorealistic losses and is a generalized optimization framework. This work investigates the IIT algorithm with the gamma correction approach to improve accuracy in response to this limitation. Our goal is to get over the drawbacks of the IIT method used alone[15]. The approved technique determines the optimal configuration by combining CLAHE+IIT, IIT+BF, and IIT+GF implying that the combination of gamma correction with the IIT method has the potential to improve image processing accuracy, particularly when it comes to modifying hazy images.

4. PROPOSED METHOD:

The proposed approach combines the Intrinsic Image Transfer (IIT) Algorithm with the Gamma Algorithm. Using the K-Means Clustering Algorithm, the input image is first split into two clusters: the sky region and the non-sky region. As mentioned in fig4 the image is then transformed into grayscale using the gamma approach after the guided filter has been applied to the sky region to guarantee that the input's side image is clear. Now, using an exemplar image (basically a pixel image) and the output of the gamma approach, the reflectance, lighting, and content of a picture may be found using the IIT methodology. Every image has a precise point that causes it to appear dull or blurry, this point may be found using the three-step gamma correction procedure.

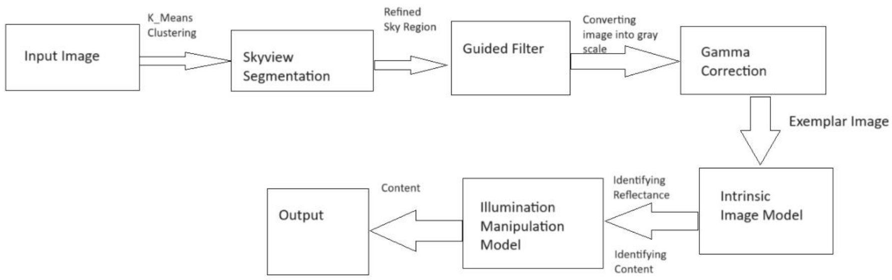

Fig 4 Block of the proposed method.

4.1. Sky Region Segmentation

For fig3.1.1 the k-means clustering method is used for segmentation after the computer first selects the vast sky region. K-means clustering divides the dataset into k-subgroups based on similarity and is a simple yet efficient method for segmenting photos. This approach sorts the data points into k different clusters, each represented by a centroid. The procedure is divided into two stages: the first calculates the k centroids, and the second assigns data points to the closest centroid as shown in fig3.1.2. The centroid location of each cluster is used to identify it, making the dataset-splitting process more effective. With an input image of size ***x×y*** and k- clusters, in (1) $\boldsymbol{c_k}$ indicates the cluster centroid and ***p(x, y)*** indicates the location of an input pixel within a cluster,

$$d = \| p(x,y) - c_k \| \text{ --------(1)}$$

Fig 3.1.1 Input image

Fig 3.1.2 Image after Applying K-Means Clustering

4.2 Guided Filter

The guided filter is used to refine the sky region once it has been segmented. The relationship between the guiding image and the filtered output is defined as follows after the sky region has been segmented and refined using the guided filter:

$$q_i = a_k I_i + b_k, \forall \in \ \omega_k \text{ -----------------(2)}$$

In (2) linear coefficient(a_k, b_k) are constants, I is the input guidance image, q is the linear transform of I in window ω_k.

The filtered output (q) is obtained as follows when noise (n) from input (p) is removed:

$$qi = pi - ni \text{---------------(3)}$$

Utilizing the cost function, reduce the difference between q and p with a linear connection in the window ω_k

$$E(a_k, b_k) = \sum_{i \in \omega_k}((a_k I_i + b_k - p_i)^2 + \varepsilon {a_k}^2) \text{------------(4)}$$

In (4), ε is a regularization factor that is used to punish large values of a_k. A linear ridge regression model is the name given to the equation above.

4.3 Gamma Correction

A crucial non-linear method for modifying the brightness level of recovered images is gamma correction. Images frequently need brightness modifications after dehazing, therefore choosing an appropriate gamma value is essential for color restoration. Three main gamma coefficients affect this process: the ratio of the average gradient, the ratio of the improved visible edges, and the percentage of saturated pixels. The gamma value increases in tandem with these coefficients. Better outcomes are usually obtained with lower gamma values.

Fig 3.2 Output image

The Fig 3.2 specifies the output image after Gamma Algorithm is applied.

4.4 Illumination Manipulation Model:

Intrinsic image transfer(IIT)[16] is a succinct method for manipulating image lighting. Three photorealistic losses content, illumination, and reflectance are specified to describe the underlying "intrinsic" layers. To replicate the spatial smoothing characteristic of picture illumination, a straightforward filtering operator is presented. Additionally, a locally linear embedding (LLE)[17]technique is developed to determine the illumination-invariant reflectance. Without requiring an explicit intrinsic picture decomposition, the enhancements offer an alternate method of optimizing image-illumination. Using a "exemplar image," a closed-form method for managing image illumination is put into practice. On a number of illumination-related tasks, the performance is confirmed both intuitively and numerically. Our IIT approach outperforms state-of-the-art methods in natural photos.

Fig 3.3 Final Output of the Algorithm

Fig 3.3 specifies the output of Gamma+IIT algorithm which identifies the illumination, reflectance and content of the image.

5 RESULTS AND CONCLUSIONS

Approximately there are twenty images in the dataset and the photorealistic losses has been identified. Subsequent to the use of intrinsic image transfer, the dehazed image proceeds through further processing stages to ensure completion. This involves multiplying the dehazed image by the corrected sky area mask in order to guarantee that only the dehazed sky region is kept while the rest of the image is kept intact. After processing, the image is saved as the output result, which shows less haze in the sky area and increased clarity. This finalization stage highlights clarity and detail in important regions, improving the image's overall visual quality. With better sky vision and less atmospheric interference, the output result is a better portrayal of the original image. With this step, the image processing pipeline is completed and a polished, aesthetically pleasing output is produced, ready for display or additional analysis.

Fig 5.1(a) Input (b) Exemplar Image (c) Gamma+IIT Image

Figure 5.1(a) shows the image input. The image is then split into two clusters using the k-means clustering algorithm: sky-region segmentation and non-sky-region segmentation. This process is repeated for the sky-region segmentation. The image's sides are identified using a guided filter, and the Gamma method is then used to convert the image to grayscale. The Gamma method's output is combined with the exemplar image (b) to identify realistic losses in the photo, which are then corrected using the LLE algorithm to create the final image (c).

PSNR(Peek Signal-To-Noise Ratio):

Peak Signal-to-Noise Ratio (PSNR) is used statistic to assess how well processed or reconstructed images compare to their original quality. It calculates the relationship between a signal's maximal potential power and its noise power.

The mean squared error (MSE) is the easiest way to define PSNR. MSE is defined as follows:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2\text{--------}(5)$$

given a noisy approximation K and a noise-free m×n single-tone picture I

PSNR = 20*log (max (max (f)))/ ((MSE)^0.5) --------------------(6)
In (6) max(f) represent the maximum pixel value of the image

SSMI(Structural Similarity Index Measure):

One popular technique for determining how similar two photos are to one another is the Structural Similarity Index Measure (SSIM). Its ability to consider structure information and perceived changes in images, rather than just comparing individual pixels, makes it especially popular in the fields of image processing and computer vision.

SSIM takes into account elements like brightness, contrast, and structure in order to replicate how people perceive the quality of an image.
Below is an explanation of the elements that go into determining the SSIM index: Luminance Comparison (L): This factor gauges how close the luminance (brightness) of the two pictures is to one another. It is computed as the average of the two images values.
Comparison of Contrast (C): In an image, contrast is the brightness variation between different objects or areas. The contrast comparison calculates how similar the two images' contrasts are to one another.
The covariance of the two images' pixel values is used to calculate it.

$$SSMI(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x 2 + \mu_y 2 + c_1)(\sigma_x 2 + \sigma_y 2 + c_2)} \quad \text{--------------------(7)}$$

In (7), μ_x and μ_y are the means of the images x and y respectively. $\sigma_x 2$ and $\sigma_y 2$ are the variances of the images x and y respectively. σ_{xy} is the covariance of the images x and y. c_1 and c_2 are constants.
In the following table (Table 1), we have compared PSNR and SSMI to the algorithms Gamma Algorithm and Gamma+IIT algorithm.

	Gamma Algorithm	Gamma+ IIT Algorithm
PSNR	27.835654293518953	28.157662773625585
SSMI	0.3152540838298061	0.8380320865438617

Table 1: Comparison of PSNR and SSMI values of Gamma algorithm and Gamma+IIT algorithm

6 FUTURE SCOPE:

The combination of the IIT method and the gamma model not only provides a general way to deal with differences in illumination between images, but also highlights how the algorithm can work its way through situations where careful adjustment is necessary. The technique allows for the accurate restoration of fuzzy photos while maintaining lifelike features by isolating intrinsic image components. Looking at cutting-edge methods for adding the gamma model to the IIT algorithm in order to increase illumination adjustments' accuracy and flexibility. Real-time processing optimization of the method makes it appropriate for applications where speed is critical, such live streaming and video processing.

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