Contrast Image Enhancement By Intrinsic Decomposition

Bhagyashree .M. Kamble[1], Pankaj H. Durole[2]
[1, 2] Dept of CSE
[1, 2] Deogiri Institute of Engineering and Management Studies, Aurangabad, MH, India

Abstract- *In this paper we are going to discuss how to enhance the quality of an image that is been degraded by uneven distribution of light. The efficacy of contrast enhancement is widely known from photography, particularly for digital photography, in which it is employed to help compensate for the physical limitations of photographic equipment in comparison with the human visual system. Intrinsic image components can be regarded as a set of images describing an image in terms of scene illumination, shape and reflectance of surfaces in the scene.The effective method to enhance the quality is by intrinsic decomposition .in Industry there is wide range of application for Decomposing an image into its intrinsic components , so it is necessary to obtain prior knowledge on reflectance and shading to solve the intrinsic decomposition problem. Intrinsic image decomposition aiming to separate an image into reflectance and illumination layers. The illumination values represent the amount of reached light. The proposed system which performs the Split Bergman algorithm for the intrinsic decomposition and adjust the illumination layer of the processed image.the proposed decomposition model is performed on the value channel in HSV space, To avoid color artifacts potential introduced by illumination adjusting and reduce computing complexity, The performance of the proposed system is evaluated by using the obtained results with the conventional decomposition methods. Experimental results shows that without effecting the texture/ boundary of an image we achieve the excellent quality of contrast enhanced image.*

Keywords- Intrinsic decomposition ,illumination ,reflectance , gamma mapping , image enhancement ,Gamma mapping.

I. INTRODUCTION

Image is the multiplication of two components namely reflectance and illumination . Intrinsic image are a mid-level representation of an image that decomposes the image into reflectance and illumination layers. The reflectance layer captures the color and textures of images Illumination is wide dyanamic range of resourse which is light. the camera captures the raw data which have variety of problems and therefore it is not likely to produce the best computer vision that's why we take careful consideration of image pre-processing. So to enhance the quality of an image we focus on the intrinsic decomposition algorithm followed by illumination adjustment to get the best result of enhanced image. In the existing system the image enhancement is performed first, a lightness-order error measure is proposed to access naturalness preservation objectively. Secondly , a bright-pass filter is proposed to determine the details and the naturalness of the image by decomposing image into reflectance and illumination. Thirdly , we propose a bi-log transformation, which is used to map the illumination to make a balance between details and naturalness. The bright-pass filter which is able to restrict the reflectance to 0 and 1. The basic idea of the bright pass filter is that, for an adjacent pixel of value a affecting a central pixel of value b, the effect is positively related to the frequency for pixels of value a and pixels of value b being neighbors all over the image. Generally, the neighbors can be defined flexibly for different applications. As the frequency is statistic and its normalized version is used as the weight of adjacent pixels in the bright pass filter, we assume there is no obvious difference between the filtering results by using different neighbors.

Correspondingly, experiments demonstrate that the filtering results obtained using four-connectivity and other neighbors, such as eight-connectivity, are similar. For simplicity, we set the neighbors of a pixel G(x, y) as a five-pixel square in four connectivity. For the pixel of value k at (x, y), N Nk,l(x, y) indicates the number of its neighbors of value l. The frequency Q(k, l) for values k and l pixels are neighbors all over the image. the illumination can beevaluated by using the bright-pass filter, based on the assumption to that of illumination is the local maxima for each pixel. For simplicity, we assume that the three color channels have the same illumination. Unlike traditional filters, we only take the neighbors that are brighter than the central pixel into account. Compared with darker areas, it is obvious that brighter areas are closer to illumination. We take the intensity L(x, y) obtained using as the coarse evaluation of the illumination and we refine it through the bright-pass filter. To get final enhanced image the mapped illumination will be synthesized with reflectance, it should not suppress the details so that it should be bright enough, and meanwhile the lightness order should can be preserved. With the histogram specification we preserve the lightness order, we map illumination through histogram specification and our task focuses on finding an appropriate shape for that specific histogram. Hence , the intensity of the images processed appears similar by histogram specification. The mapped illumination should look a bit different based on different intensity of input images. As log-shape histogram specification can render the mapped illumination bright enough, we represent the difference by slightly increasing the pixels of low gray levels, according to the gray-level distribution of the input illumination. Experimental results shows that it performs well with the weight of the histogram set as the log of illumination. The relative state of lightness in different local areas of the mapped illumination is the same as that of the original illumination, it is easy to verify the relative order for the pixels, whose reflectance is 1, does not change. In addition, according to the definition of the hue in different color space, such as HSI and HSV, the hue value of a pixel is dependent on the ratio of its three color values (R, G, and B). As the ratio of the three color values show no change before and after enhancement, the proposed algorithm is able to preserve the hue values of the image.

DISADVANTAGES:

- Contrast loss in the enhanced image due to incorrect estimation.
- Computational complexity is high.
- it may introduce slight flickering for video applications in case that the scenes vary apparently.

In that proposed system we enhance the image by the intrinsic decomposition method. The proposed system which performs the Split Bergman algorithm. In that the illumination and reflectance layer of the image is extracted and adjust the illumination layer of the processed image. To avoid potential color artifacts introduced by illumination adjusting. For that illumination adjusting the illumination layer is adjusted by using the gamma mapping function. After computing the reflectance and illumination layers, the following task is to adjust the illumination values to enhance image details. The system presents the widely used mapping functions, including Log, Sigmoid and Gamma functions. It can be observed that these functions all lighten dark areas while preserving the lightness order. However, they also compress intensities in bright areas, i.e. the variation of large intensities is reduced. It will lead to the loss of details in bright areas, especially for the Log and Sigmoid functions. Therefore, we adopt the Gamma function to adjust illuminations And the intensity adjusted image is integrated with the reflectance layer and then the contrast limited adaptive histogram equalization is performed for the histogram equalization and then the converted HSV image is get back into the original RGB image.

This paper is organized as follows In Section II, The proposed system which performs the Split Bergman algorithm for the intrinsic decomposition and adjust the illumination layer of the processed image.In Section III Analysis and comparison of experimental results Section IV is the conclusion.

II. PROPOSED SYSTEM

Pre-Processing Model

Image pre-processing can be termed as operations on images at the lowest level of abstraction. These operations converts the extracted data into digital form so that we can enhanced the image by utilizing different measures. The aim of pre-processing of image is to improve the data that suppresses undesired distortions or enhances some features of an image relevant for further processing and analysis task. In image pre-processing there is redundant use of images. Nearby pixels corresponding to the real object have the same or similar brightness value. If a distorted pixel is picked out from the image, we can restored it as an average value of nearby pixels. Image pre-processing methods are classified into different categories, according to the size of theneighborhood pixels that is used for the calculating brightness of a new pixel . The preprocessing is step taken before the major image processing task. Here the problem is to perform some basic tasks in order to render the resulting image more suitable for the job to follow. In such case it may involve different enhancement techniques such as enhancing the contrast, removing noise, or identifying regions likely to contain the postcode.

The main aim of pre-processing is to improve the image data that suppresses unwilling distortions or enhances some features of image important for further processing, although geometric transformations of images. The functionuigetfile is used to get the image from the dataset. After getting the input image, the pre-processing step is been performed. In that the input image is resized into 256 X 256 sized image for the processing , Fig 2 and Fig 3 shows one of the example of input and resized image. Likewise all the images in the dataset was preprocessed. Fig 1 shows the flow diagram of the proposed system. The preprocessed images will have some noise which can be removed for the further processing of the image. Image noise is the most apparent in image regions with low signal level such as shadow regions or under exposed images.

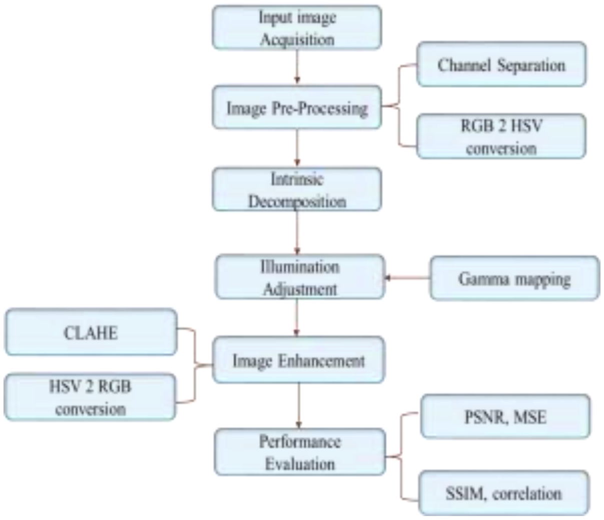


Fig 1 . Flow diagram of proposed system

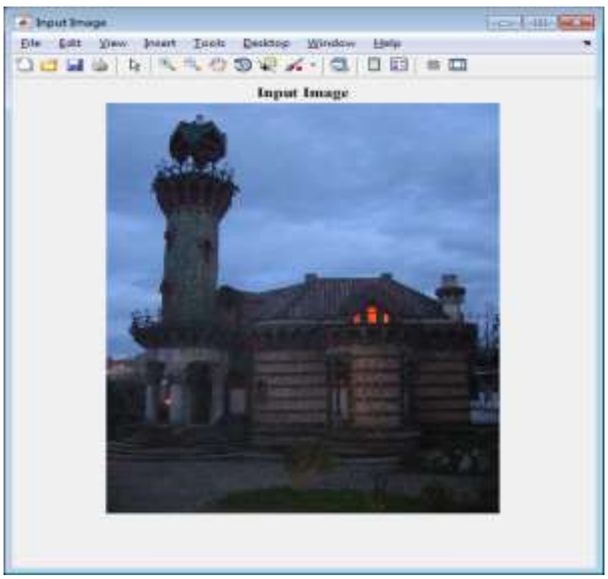


Fig 2.The above figure shows the Input Image

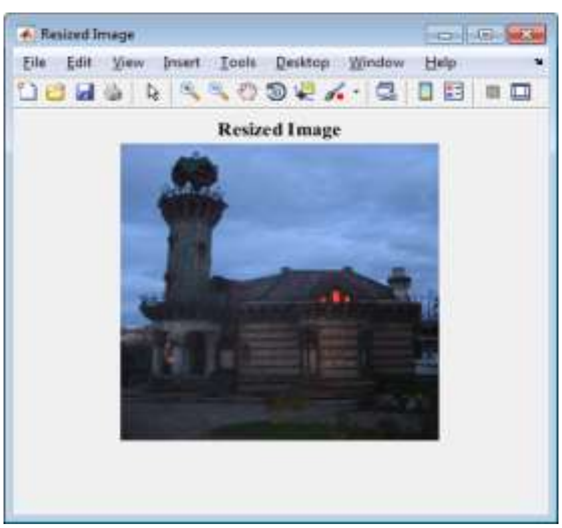
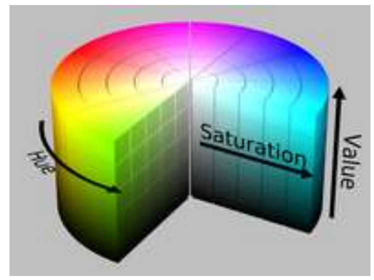


Fig 3. The above figure shows the Resized Image

RGB to HSV Conversion:

The HSV model is the alternate representation of RGB model. HSV describes colors similarly to how the human eye tends to perceive color. RGB model can be defined as of a combination of primary colors, whereas, HSV model is describe as comparisons such as color, amount of white light mixed with color and intensity.



Hue represents the color type as preserved by the observer. It can be described in terms of an angle on the above circle as shown in fig . This model contains 360 degrees of rotation, the hue value is a ranged from 0 to 255, with 0 being red. • Saturation is vibrancy of the color we can term as the amount of white light mixed with hue . Its value ranges from 0 to 255. The lower the value of saturation, the more color of gray is present, causing it to appear faded. • Value is the brightness of the color we can term it as chromatic notice of intensity ,Fig 5 shows V channel of an image. It value ranges from 0 to 255, with 0 coded as completely dark and 255 coded as fully bright. • White HSV value ranges is as 0-255, 0-255, 255. Black HSV value range as 0-255, 0-255, 0.HSV image is as shown in Fig 4. The description for black and white is the term, value. The hue and saturation level do not show any difference when the value is at max or min intensity level.

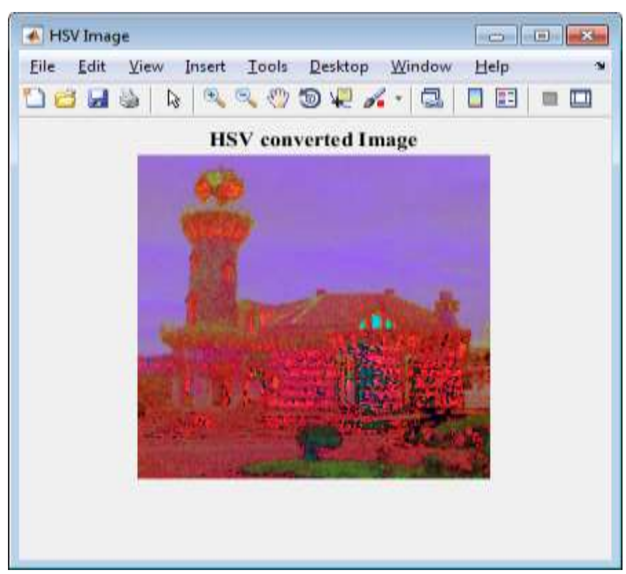


Fig 4.The above figure shows the HSV converted Image

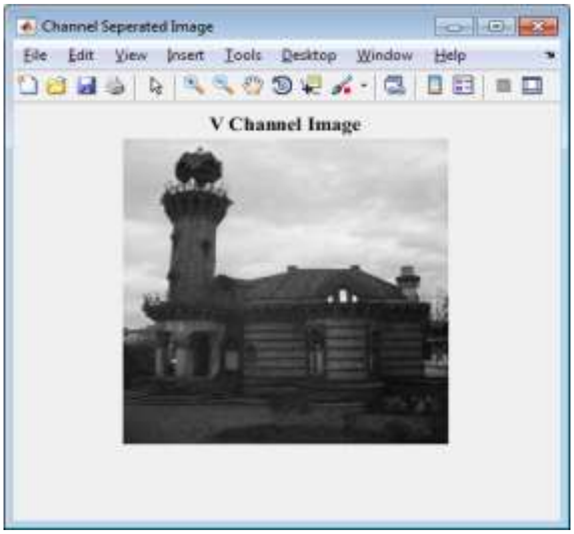


Fig 5.The above figure shows the V Channel Image

Intrinsic Decomposition Model:

Intrinsic image decomposition aims to decompose one image into reflectance and illumination layers, namely to solve the equation V = L · R (“·” represents pointwise multiplication.). As it is highly ill-posed, we propose to introduce the intrinsic decomposition priors as our constraint, including: 1) Neighboring pixels with similar colors should have the same reflectance. 2) Neighboring pixels have similar illumination. Therefore, we formulate the intrinsic decomposition problem as a minimization problem of the energy function. The first and second terms are regularized on the reflectance(Fig 6) and illumination(Fig 7) layers, respectively. The third term is the data term to ensure the reliability of decomposition. Different from previous equality constraint in intrinsic decomposition, we propose to utilize the norm penalty to tolerate noise, since the dark areas may be very noisy. Otherwise, noise would be decomposed. The last term is utilized to constrain the scale of l, where the set to the chromatic normalization value. The E r(r) term constrains the reflectance layer to be piecewise constant according to the color similarity. For pixels with similar colors, we increase the weight values to penalize the difference between ri and rj. After computing the reflectance and illumination layers, the following task is to adjust the illumination values to enhance image details. The system presents the widely used mapping functions, including Log, Sigmoid and Gamma functions. It can be observed that these functions all lighten dark areaswhile preserving the lightness order. However, they also compress intensities in bright areas.

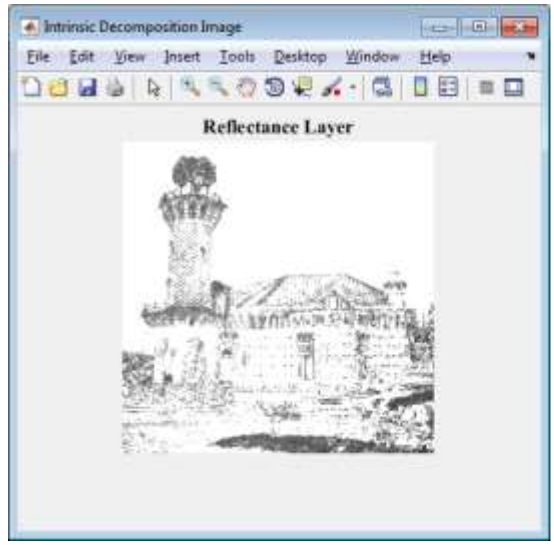


Fig 6. Reflectance Layer of image

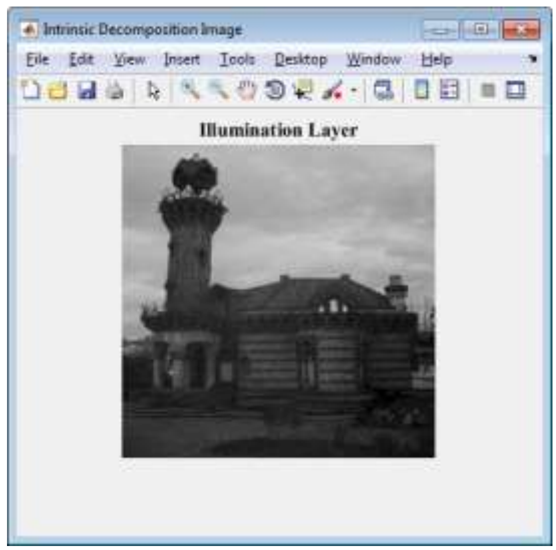


Fig 7. Illumination Layer of image

Illumination Adjustment Model:

The goal of illumination correction is to remove uneven illumination of the image caused by sensor defaults, non-uniform illumination of the scene, or orientation of the objects surface. After computing the reflectance and illumination layers, the following task is to adjust the illumination values to enhance image details presents the widely used mapping functions, including Log, Sigmoid and Gamma functions Fig 8 shows illuminated adjusted image. It can be observed that these functions all lighten dark areas while preserving the lightness order.However, they also compress intensities in bright areas, i.e. the variation of large intensities is reduced. It will lead to the loss of details in bright areas, especially for the Log and Sigmoid functions. Consequently, the adjusted illumination is multiplied by the decomposed reflectance R, generating the enhanced V channel image Ve. Since the mapping function is intended for enhancing global contrast, we further adopt CLAHE to improve local contrast of Ve. The enhanced result is denoted as Vˆ e. Then we transform the enhanced HSV image to RGB space, generating the final result.

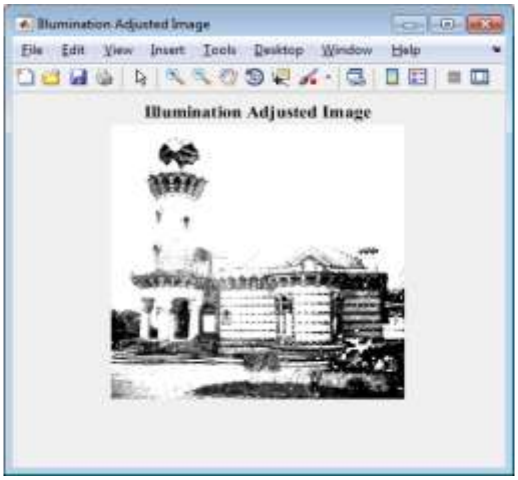


Fig 8. Illumination adjusted image

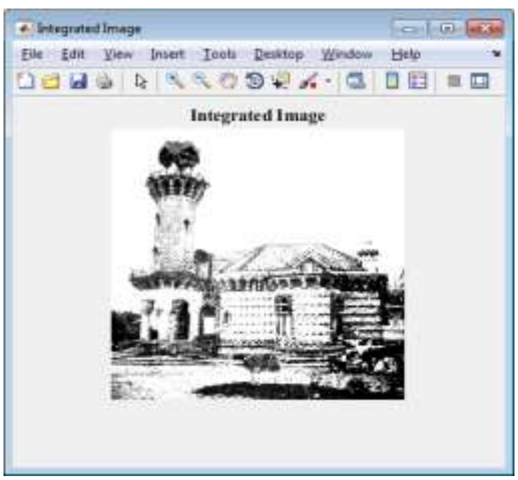


Fig 9. Integrated image

Fig 10. Enhanced image

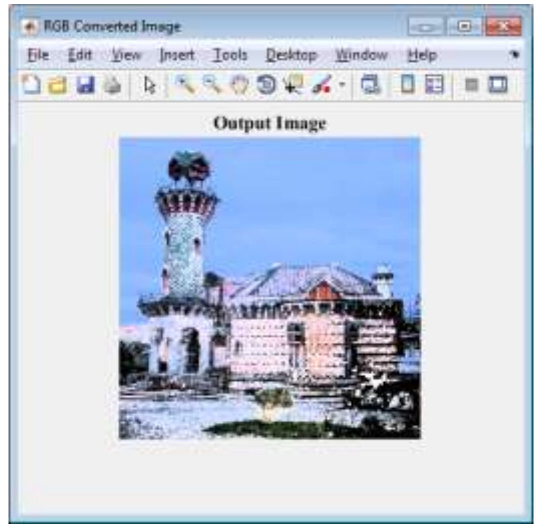


Fig 11. Output image

III. PERFORMANCE EVALUATION:

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is theerror introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec and same content.

The structural similarity (SSIM) index is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. The first version of the model was developed in the Laboratory for Image and Video Engineering (LIVE) at The University of Texas at Austin and the full algorithm was developed jointly with the Laboratory for Computational Vision (LCV) at New York University. SSIM is used for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measurement or prediction of image quality is based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods such as peak signal-to-noise ratio (PSNR) and mean squared error (MSE). The MSE is a measure of the quality of an estimator—

it is always non-negative, and values closer to zero are better. The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance of the estimator. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root-mean-square error or root-mean-square deviation (RMSE or RMSD), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard deviation. Digital image correlation and tracking is an optical method that employs tracking and image registration techniques for accurate 2D and 3D measurements of changes in images. This method is often used to measure full-field displacement and strains, and it is widely applied in many areas of science and engineering, with new applications being found all the time. Compared to strain gages and extensometers, the amount of information gathered about the fine details of deformation during mechanical tests is increased

Comparison table

Images	MSE	PSNR	CORELATION	SSIM	ENTROPY
1	0.0640	60.1024	0.4704	0.0130	6.5401
2	0.0789	59.1958	0.6201	0.0054	5.8983
3	0.0348	62.7467	0.7754	0.0196	5.5521
4	0.0753	59.3966	0.8809	0.0549	5.5564
5	0.1033	58.0257	0.8693	0.0075	6.6664

Image 1

Image 2

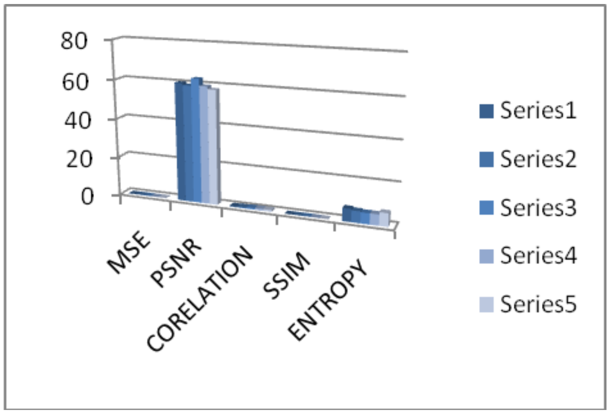
Image 3

Image 4

Image 5

We take different images with different intensity of light and calculated the numerical values of different images as shown in table 1.

Different performance measuring parameters like MSE , PSNR , CORELATION , SSIM and ENTROPY for different images is shown below in graphical format



IV. CONCLUSION

The proposed effective method to enhance images by estimating illumination and reflectance layers through intrinsic image decomposition. On the other hand, we constrain the reflectance layer to be piecewise constant according to the color similarity. On the other hand, the illumination layer is enforced to be locally smooth. Since the decomposition model is nonconvex and non-differential, we perform the Split Bregman algorithm to iteratively solve this problem. After decomposition, we perform Gamma correction on the illumination layer to adjust the illumination intensity of the image. Then we perform the contrast limited adaptive histogram equalization CLAHE to further enhance local details. The performance of the system shows that the proposed system performs better than the conventional decomposition methods. In future Discrete Wavelet Transform is applied to the Saturation (S) components, and the decomposed approximation coefficients are modified by a mapping function derived from scaling triangle transform. The enhanced S component is obtained through Inverse Wavelet transforms. this is future work

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