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CONTRAST ENHANCEMENT USING ADAPTIVE THRESHOLD BASED DYNAMIC RANGE ADJUSTMENT IN LUV COLOUR SPACE

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Abstract

This paper presents a method for contrast enhancement of low light images. The images captured in dark or during night-time cannot be properly perceived by human eye because quality of these images is severally degraded due to lack of clarity. Many image enhancement methods are used widely in image processing to enhance such images. In this proposes an efficient method to enhance the contrast of a low light image by adjusting dynamic range with four steps. Firstly, the low light image is divided into two parts dark part and bright part based on histogram of luminance map of the image. Secondly both the parts are gamma corrected using suitable gamma function. Third, to combine the enhanced regions, fusion method is used and finally to recover the original colour image, colour restoration method is used. In literature the threshold used to divide low light image into two parts is taken as constant (0.5), the proposed method makes this threshold adaptive to the low light image contents by using threshold as exposure, mean of the luminance or median of luminance. Also further the luminance map consideration is proposed to be even proportion of individual colour components rather than weighted proportion. The proposed novel method with image adaptive threshold computation and evenly proportionate luminance components gives better performance as objectively tested with 30 images testbed and NIQE and Entropy as Image Quality Evaluator. Above experiments show that the proposed method gives better results as compared to existing ones. In this method natural scenes like leaves of trees, water bodies can be enhanced to greater extent.

Keywords: Gamma correction, Image Enhancement, Kekre's LUV colour space, Low light image, Luminance.

1. Introduction

People have been capturing many images in day-to-day life. These images are often corrupted by changes in atmosphere or may be due to poor quality image capturing devices or because of lack of sufficient illumination needing image enhancement further. The purpose of Enhancement of Images is to make the objective images more suitable for particular application than the original images. Image enhancement has wide range of applications in areas like remote sensing, medical image processing, digital photography, video processing applications, satellite image analysis, atmospheric sciences, object detection, face recognition and many more. Enhancement of image is mainly established on which technique is to be adopted to correct the image like removing unwanted noise, improving contrast of an image, de-blurring, smoothing, sharpening and edge enhancement. Out of which most prominent way is improving contrast of an image which in turn leads to many methods and algorithms, trying to make the image more pleasant to human visual system. The images captured in poor illumination appear darker, this is because of the insufficiency of light and high noise levels which adversely not only affect the usual colours of image but also the contrast of the image. This leads to the demand of enhancing these low contrast darker images for better visual quality to extract more information from such images.

Improving contrast of an image has most important role in night vision area as well. Improving contrast is reliable factor in deciding the image quality. The image is not considered to be of good quality if its contrast is very low or very high. So, to improve the quality of low contrast images enhancement can be done either globally or locally. In case of global enhancement approach these poorly illuminated images are contrast corrected using global contrast enhancement and their data is well-defined at global level in comparison with the original image. Also, these images which are low in contrast can be improved in quality that to in specific area using local enhancement methods, where the focus is given on the information available at local level as related to the original image.

In today’s world for night-time navigation and military surveillance, most images captured by devices using sensors are not often fully dark but most of the times they contain mixture two regions as dark and bright regions. These scenes usually occur where the streetlights are glowing at night and signposts present besides the roads will be the part of a picture, which ultimately creates a challenge for many image enhancement and night vision researchers, as it is very difficult to find the uniformity in contrast improvement of dark region without affecting the details and contrast in bright region in low illuminated images with mixed dark and bright regions.

For such a low contrast darker images with miscellaneous dark and bright regions neither local nor global contrast enhancement method only could be applied for contrast enhancement, needing the methods with ability of separation of these regions and then according to contrast adjustment.

These image contrast enhancement techniques are categorized into spatial domain and transform domain. The techniques come under spatial domain, contrast enhancement is applied directly on the pixel level of the image and in the second category an image is converted in transform (frequency) domain and then it is been operated [1].

The organisation of the paper is made in 5 sections. The existing work done for enhancing low contrast images is discussed in section 2. Section 3 includes detailing of proposed Contrast Enhancement using Adaptive Threshold based Image Dynamic Range Adjustment in Kekre's LUV Colour Space technique. Section 4 gives experimental results of the proposed and few of the existing contrast enhancement methods with the comparative discussions. The works done is summarized as conclusion in section 5.

2. Related work

Image Contrast Enhancement mainly are proposed into three prominent approaches as contrast enhancement in spatial domain, contrast enhancement in frequency domain and hybrid methods of contrast enhancement.

Methods belonging to spatial domain mostly can be included in the approaches like Histogram Equalization approach, retinex approach and Gamma Correction approach.

The most popular technique amongst researcher for low light contrast image enhancement in spatial domain is Histogram Equalization (HE) [1], as it is simple and can be implemented very fast. Histogram Equalization identifies the most frequent occurring pixel intensity values and try to spread them uniformly through the image. Low light images contain both dark and bright regions and after applying histogram equalization technique the excessive over enhancement of bright region appears. This drawback led the modification of histogram equalization techniques, as Adaptive Histogram Equalization (AHE) [2] and Contrast Limited Adaptive Histogram Equalization (CLAHE) [3] methods. Later is an improvement of former. These two methods work by different histograms on different regions of an image and which are used to get better the contrast of an image. Recent work published based on AHE and CLAHE are in 2019. Sirajuddeen and Tripathi, modified conventional HE as Adaptive Histogram Equalization based on probability density function [4]. This method is focused on modified probability density function along with expected value of image intensity (Adaptiveness) also it can resolve the artefacts present in traditional histogram equalization method.

The drawback of this method is that over bright spots such as streetlights cause the scene to be unpleasant for visual quality. This method is modified version of Adaptive Histogram Equalization method (1987). Shi et al. [5] has given a contrast enhancement method using gamma correction in which Lab colour space is used to remove sand dust and correction in colour. The L channel of input image is enhanced using gamma correction along with contrast limited adaptive histogram equalization and the chromatic components are recovered by grey world-based colour correction method. However, this method only enhances visual of sand-dust images but unable to remove dust haze from the image. The main limitation of these methods is they modify the average brightness of poorly illuminated image to central level of the dynamic range that causes effect in intensity saturation and frustrating artefacts. Also, these methods are unable set a proper threshold for limiting contrast and have need of a user input.

Many methods were suggested to overcome these drawbacks. An attempt was made by Kim by proposing "Brightness preserving bi histogram equalization" (BBHE) [6] to enhance the contrast of an image with mean brightness preservation. The image is divided into two halves based on mean then these two parts have been equalized separately. Recent modification done in [6] is proposed by Yao et al. in

"Brightness preserving, and contrast limited bi-histogram equalization for image enhancement" (BPCLBHE) method [7] in which the image is divided into two halves based on mean and then contrast limited technique is applied separately on both the parts to enhance the contrast of image. Wan et al. proposed an extension and comparatively better method than BBHE as "Dualistic sub image histogram equalization" (DSIHE) [8], where the image is separated in two sub histograms having same number of bins and median is used for division instead of mean brightness. DSIHE has been claimed to have given better result than BBHE. The latest development based on DSIHE is given by Yao et al. proposing "Image Enhancement Based on Equal Area Dualistic Sub-image and Non-parametric Modified Histogram Equalization Method" (DSINMHE) [9], where the division of image is done based on median value of input image and then they are modified by histogram equalization technique to maximize entropy and to control over brightness of an image.

Chen and Ramli, have given a CE method named "Minimum mean brightness error bi-histogram equalization" (MMBEBHE) [10], which gives importance on the preservation of average brightness. MMBEBHE is an advancement on BBHE, which find out AMBE (absolute mean brightness error) for 0 to L-1 grey levels. Kansal et al. [11] used the logic of bi-histogram equalization and modified a CE method named "Enhancement of Image using Maximum Entropy Bi-Histogram Equalization". In this method the flattening of histogram is done based on selection of grey level to obtain maximum entropy. Chen and Ramli [12] again introduced another method referred as "Recursive mean-separate histogram equalization" (RMSHE), which repetitively executes the BBHE where there is a separation of histogram into two different parts, by considering average of input brightness and independently on each part of the histogram BBHE is performed. Shanmugavadhivu et al. [13] segmented the histogram of the input image in two parts based on mean and then to each sub histograms weighting constraints are applied using Particle Swarm Optimization for enhancement of low contrast images as an advancement in [12].

Sim et al. [14] alike to RMSHE well-known as "Recursive sub-image histogram equalization" (RSIHE). In RSIHE the histogram is divided on basis of median brightness against of average brightness. These methods are unable to give the technique for adjusting level of enhancement. In recent era 2017, Zhuang and Guan separated histogram of input image in four parts based on mean and variance of luminance [15]. Each segmented bean is modified and equalized separately and the final image is obtained by concatenation of all sub parts of an image. To overcome this problem new set of methods proposed by Wang and Ward [16], Kim and Paik [17], Ooi et al. [18] which control the rate of enhancement and restore the originality in brightness. To control highest intensity value pixels of histogram, histograms with higher value than given threshold value are clipped. Clipping threshold values can be determined using different approaches. In recently followed algorithms based on [16-18], Tuba et al. [19] used Bat algorithm for enhancement of low contrast images with improved thresholded histogram techniques in 2016. In 2017, Reddy et al. [20] used Otsu thresholding for contrast enhancement to get bimodal image. With similar logic of thresholding of input image Bhandari et al. [21] proposed a new technique based on social spider optimization with weighted Otsu thresholding. This method separated image histogram in two parts based on Otsu thresholding then these parts are assigned with weights to control the level of enhancement.

These methods are directly applied on image pixels and are simple and easy for implementation relatively, hence many variations of these methods have been extensively worked out for image contrast enhancement. But these methods have few disadvantages. Low contrast image consists of dark as well as bright regions. So, in histogram-based approach methods bright region gets over enhanced (for example streetlights during nighttime). Also, indiscrimination in resultant image is observed and sometimes it increases contrast of background noise, while decreasing usable scenes.

Another approach towards contrast enhancement of low light images is retinex theory. Some of the algorithms based on retinex theory consider reflectance as improved result by approximating and eliminating illumination. The algorithms single scale retinex (SSR) [22] and the multi-scale retinex (MSR) [23] do separate reflectance and illumination by using local Gaussian filters. Details and luminance of an image can be enhanced by removing the impact of illumination on original image, but the end results found are often over-enhanced by such center/surround approaches. To overcome the above drawback Jobson et al. [23] proposed MSRCR method. Meylan and Susstrunk [24] proposed the adaptive retinex-based method, which successfully reduced halo artefacts using adaptive filter to the luminance channel. The recent work done on retinex method is given in “Power-Constrained Contrast Enhancement Algorithm” (PCCEA) (2014). Multiscale retinex is used for OLED Display to find the proper gain so that it can be used for getting better visual quality with regular power-saving in the absence of the artefacts of flickering as suggested by Yeon-Oh et al. [25]. “Image enhancement for outdoor long-range surveillance using IQ-learning multiscale retinex” by Liu et al. [26]. It focuses on the image quality of the image due to the complex atmosphere. Liu et al. used MSR based on the image quality learning so that they can increase the visual quality of images. Seonhee et al. [27] introduced “Low-Light Image Enhancement Using Variational Optimization-based retinex model”. to enhance the low-light images with lower noise in dark region. It utilizes a variational retinex model by not disturbing the details in original image.

Advantages of retinex methods are removal of halo effects because of use of adaptive filters and improvised visual quality of original colours due to the colour restoration technique used in retinex methods. Though better results are obtained, this method still has some drawbacks like these fails to enhance more weakly illuminated regions of low contrast image also these methods are complex.

Chiu et al. [28] suggested a technique which can automatically improve contrast of low light images using indirect method of enhancement using gamma correction to luminance channel. Haung et al. [29] presented a technique based on automatic transformation to advance brightness of dark images by using technique of gamma correction along with luminance pixels probability distribution. To correct the poorly illuminated image, this method considers the differences between each frame as temporal information to decrease complexity in computation. Yang and Li [30] proposed a method for dynamic range adjustment and low contrast image enhancement by separating luminance component in YCbCr colour space.

Gamma correction methods gave better results in spatial domain category, the reason for this is an input image is separated into luminance and chromaticity parts which avoids colour distortion in colour images. Further dark and bright parts are separately enhanced in these methods.

Defiantly these methods are better in spatial domain, but they have some shortcomings as well. These methods used YCbCr colour space which has some under enhancement regions in results. Here threshold used to separate dark and bright parts is fixed and which is not image dependant. Also, gamma correction methods are unable to enhance natural textures like leaves of trees, water bodies, etc.

To overcome problems of spatial domain, researchers have tried to use methods in frequency domain as well. Algorithms available in frequency domain are based on Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) are elaborated here.

A few methods for low contrast image enhancement which works in frequency domain like Demirel et al. [31, 32] proposed methods based on scaling the singular values, these are not suitable for low contrast images with mid-range of brightness. Atta and Ghanbari [33] and Atta and Kader [34] give better performance for images with mid-range of brightness as compared to previous methods. A combination of histogram modifications and Discrete Cosine transforms (DCT) or Discrete wavelet transform (DWT) domain have been found in recent times [35-38]. In all these methods, the AC coefficients do first get scaled and then modifications in DC coefficients are done to improve contrast of low light image. The DC and the AC coefficients are scaled using same scale factor used in the DCT domain for contrast enhancement as proposed in [35], the same scaling factors the chromatic components also to improve quality of poorly illuminated colour images. The advance modification of DCT component is used in “Efficiency of texture image enhancement by DCT-based filtering” [36]. In this research the influence of textural properties on efficiency of image enhancement by noise suppression for the posterior treatment is given. Among possible variants of denoising, filters based on discrete cosine transform known to be effective in removing additive white Gaussian noise are considered.

Tang et al. [37] used wavelet domain a multi-scale contrast measure to improvise mammogram’s image contrast but, this technology failed to focus on the improvement of illumination present in background. An approach for the improvement of contrast of dark images based on wavelet coefficient’s local statistics proposed in [38]. Combining denoising along with enhancement logic was implemented on wavelet coefficient at high-pass. After that, the low-pass coefficients are given using CLAHE (“Contrast limited adaptive histogram equalization”) [3] for improving the illumination of background. This method requires an extra algorithm for denoising which means to remove noise due to adjustment wavelet coefficients at high-pass. Image contrast and brightness are improvised in quality by approximating the scaling coefficient’s scale factors and three sub-factors like shrinkage factor, locality factor and the scale factor) [39, 40]. A suppression factor to suppress noise is also needed in this method.

Using transforms for improvement of low contrast images have advantages of good under enhancement compared to spatial domain also by using DWT it can capture both frequency and time information.

Pitfalls of transferring an image into transform domain are, while working in high frequency band noise is generated causing distortion in output image. Also, problem of colour pigmentation is observed in transform domain.

Also, several algorithms were proposed to enhance low contrast images using fusion method. Image fusion-based methods [41-43] focused to merge related information from many images belonging to similar nature of scene to obtain the fused image, containing more information compared to the individual images. Before image fusion this model generates several "pseudo images" or "virtual images" from one input image. Hsieh et al. [41] has fused the HE enhanced and original input image using a linear function. Pei et al. [42] fused the discrete wavelet transform (DWT) coefficients of two images, first one is generated as HE enhanced image and the second image is Laplacian sharpened image, to obtained enhanced fused image. Lim et al. [43] introduced a method which has the mapping function based no intensity, applied to input image to produce multiple images with assorted exposures. Recent work on [43] is proposed in [30] as discussed earlier. Fu et al. [44] gave an algorithm using morphological closing where an observed image is decomposed in reflectance image and illumination image and then derive two inputs which are going to represent contrast based enhanced output of the first illuminative decomposed using sigmoid function and AHE (adaptive histogram equalization). The use of assigning two weights related to the inputs, give an illumination adjusted by fusion of the resulted inputs along with the respective weights based on fusion of a multi-scales. As in this method diverse images have been fused, they bound to give good results of enhancement. Also, there is a freedom of using methods from both the domains but the problem in this method is the discontinuities observed in resultant images after using transforms.

3. Proposed Work

To correct or enhance the contrast of an image Gamma transformation method is used in most of the applications. The selection of proper value of gamma is very crucial for a particular region of an image to get details of an image which are unexposed in low contrast scene. For example, if we want to increase the brightness of a dark region small value of gamma (< 1) is used. On the same platform a greater value of Gamma (> 1) is appropriate for contrast improvement of the much brighter scene. The details in the two underexposed and over-exposed regions of an image must be enhanced for this purpose a modified method is proposed in this paper for enhancement of low light images with mixed instances of darker and few over bright regions using gamma correction-based approach.

The block diagram of proposed Contrast Enhancement using Adaptive Threshold based Image Dynamic Range Adjustment in Kekre's LUV Colour Space is as given in Fig. 1. At first, the given RGB image is separated into Luminance and Chromaticity parts to protect the colour of original input image. After that the luminance channel is normalized in the range [0-1]. Then the luminance channel is separated into two parts viz. dark and bright parts using computed threshold.

This paper proposes novel image adaptive threshold computation approach where threshold computed is dependent on the luminance values of image itself to have better and more relevant separation of dark as well as bright regions of the image. The separate gamma corrections are applied to these dark and bright sections of image according to the distribution of grey value luminance channel. These images after gamma correction are then improved by locally operated operator and further fused in an integrated luminance map with the reference of brightness at local level.

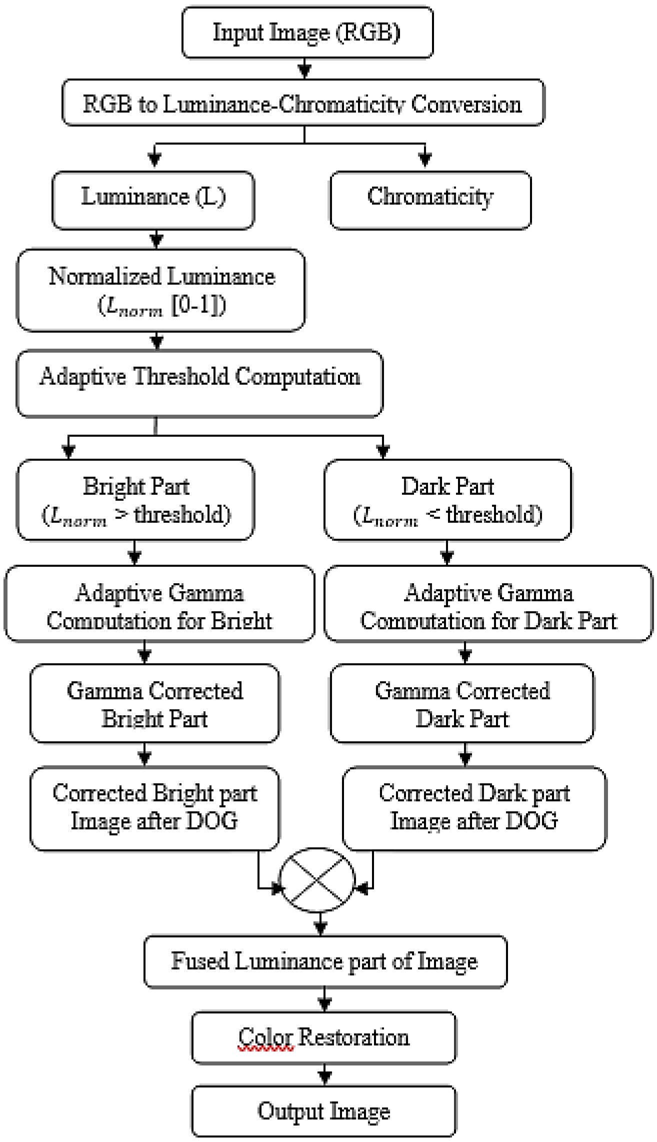

Fig. 1. Block diagram of proposed contrast enhancement using adaptive threshold-based image dynamic range adjustment in Kekre's LUV colour space.

In the final step restoration of the colour enhanced image is done. To separate the luminance and chromaticity from RGB input image in original Yang et al. [30] the YCbCr colour space was considered. The paper proposes the use of Kekre's LUV colour space [45] for this purpose as an important modification. Also, the novelty of the proposed method is computation of image adaptive threshold for separation of normalized luminance into dark and bright parts which in Yang et al. [30] was taken as constant 0.5. Here the threshold adapts to the normalized luminance of input image as mean or median or computed exposure.

3.1. Luminance-chromaticity colour space

The low contrast input image is firstly converted into luminance-chromaticity colour space in the method of contrast enhancement used here. Yang et al. [30] used YCbCr colour space and the proposed method uses more even luminance in form of the Kekre's LUV colour space [45].

By converting RGB to YCbCr colour space the luminance component Y can be obtained by Eq. (1).

$$Y = \mu 1 * R + \mu 2 * G + \mu 3 * B \tag{1}$$

where, $\mu 1 = 0.299, \mu 2 = 0.587, \mu 3 = 0.144$.

In RGB to Kekre's LUV inter conversion can be used to obtain the even luminance by Eq. (2).

$$L = n1 * R + n2 * G + n3 * B \tag{2}$$

where, $n1 = n2 = n3 = 1$.

3.2. Luminance normalization

For various low light images, the dynamic ranges of these images may vary at a large extent. So, to overcome the incoherent dynamic ranges of these input images, the luminance channel 'L' must be normalized. The normalized luminance 'L_{norm}' is the image containing all the pixel intensities between 0 to 1 values only. Thus, the luminance range L is compressed between 0 and 1 as L_{norm}.

3.3. Adaptive Threshold Computation

Yang et al. [30] considered a fixed value of threshold as 0.5 for separation of dark and bright parts of luminance. But it fails for some natural scene of image like leaves of trees, water bodies etc. The proposed method has considered different threshold values as computation of mean as $ia_{thr_{mean}}$ (Eq. (3)), computation of median as $ia_{thr_{median}}$ (Eqs. (4) and (5)) and computation of exposure as $ia_{thr_{exposure}}$ (Eqs. (6) and (7)), for a low contrast image of size *m*n* adapting to the luminance of image,

$$ia_{thr_{mean}} = \frac{1}{m*n} \sum_{y=1}^{n} \sum_{x=1}^{m} L_{norm}(x, y) \tag{3}$$

$$cL_{norm_{(1:m*n)}} = L_{norm}(:) \tag{4}$$

$$ia_{thr_{median}} = sorted\ cL_{norm}\ (xp), \quad xp = \frac{m*n}{2} \tag{5}$$

$$exposure = \frac{1}{T} \frac{\sum_{k=1}^{T} h(k)k}{\sum_{k=1}^{T} h(k)} \tag{6}$$

$$ia_{thr_{exposure}} = T(1 - exposure) \tag{7}$$

where $h(k)$ is the image histogram and T denotes the total gray levels. Also, the exposure parameter X_a is given, providing the value of boundary of gray level which divides the image in two parts over-exposed and under-exposed sub images.

3.4. Gamma correction

Firstly, normalized luminance channel L_{norm} is separated out with Bright (L_{norm} > computed adaptive threshold) and dark part (L_{norm} < computed adaptive threshold) by applying proper threshold values. These threshold values may be fixed as suggested by Yang et al. (2018) [30] and YCbCr space is used instead of Kekre's LUV. Here in this paper, we have modified the method given in [30] by changing threshold value and colour space. Firstly, the threshold is kept at fixed value (0.5) and then luminance part is divided into bright region (L_{norm} > 0.5) and dark region (L_{norm} < 0.5).

Later instead of fixed threshold value, in proposed method mean, median and exposure [46] can be used as threshold also instead of YCbCr colour space Kekre's LUV colour space [45] is used. By applying different thresholds, luminance image can be separated into bright part (L_{norm} > computed adaptive threshold) and dark part (L_{norm} < computed adaptive threshold). After that gamma correction is applied on these parts.

$$Out_{Image}(x,y) = (In_{Image}(x,y))^{\gamma} \tag{8}$$

where In_{Image} and Out_{Image} are input and output images, respectively.

It is observed from the gamma correction that low value of gamma, i.e., (γ < 1) improves brightness and the contrast of the dark region in image, but it may skip pixels with high intensity (bright pixels) from image. On the contrary, for higher gamma value, i.e., (γ > 1) can improve the over bright regions of image but may skip some dark region. Here the valuable point is to decide suitable parameter (γ) adjusting to various regions of given image.

Here in this paper automatic gamma selection is used [30] based on histogram of luminance, for this there is a need of two diverse gamma curves to enrich bright and dark regions of the same image having under exposed regions are selected for normalized luminance channel (L_{norm} whose value ranges between 0 to 1) also histogram of image is subdivided into two parts with the varying computed adaptive threshold. Further std_L and std_H are used as standard deviation of pixels for dark part, i.e., (pixels having L_{norm} < computed adaptive threshold) and bright set, i.e., (pixels having L_{norm} > computed adaptive threshold) respectively. Next is to set to expected values of median for pixel distribution in bright and dark sets respectively [30] in an image, as shown in Eqs. (9) and (10).

$$Med_L = \frac{1}{3} + std_L \tag{9}$$

$$Med_H = 1 - std_H \tag{10}$$

Note that the 1/3 and 1 are the bases of two expected medians, while std_L and std_H are used for fine tuning the expected medians as per given histogram. These settings are dependent on the presumption that the dark pixels are predominant in night images, and this assumption can be easily determined when performing various tasks.

For simplicity here the notations B_{part} is used to denote bright part having pixel values greater than threshold (i.e., B_{part} is the region contains pixels with $L_{norm} >$

0.5 /mean/median/exposure) and D_{part} is a part having pixel values less than threshold (i.e., D_{part} is the region contains pixels with $L_{norm} <$ 0.5/mean/median/exposure). The possible range of γ [30] for both bright and dark part can be selected as,

$$\gamma_B = arg_\gamma \ min(|med(B_{part})|) - Med_H, \gamma \in \{1,1.1, \dots .10\} \tag{11}$$

$$\gamma_D = arg_\gamma \ min(|med(D_{part})|) - Med_L, \gamma \in \{0.1,0.11, \dots 1\} \tag{12}$$

where $med(B_{part})$ and $med(D_{part})$ computes the median value of bright part as well as dark part, respectively.

From Eqs. (13) and (14) the gamma values can be obtained and then luminance part of an image is subjected to gamma correction. Eqs. (13) and (14) give enhanced and more visible bright and dark parts.

$$L_B = (L_{norm}(x,y))^{\gamma_B} \tag{13}$$

$$L_D = (L_{norm}(x,y))^{\gamma_D} \tag{14}$$

3.5. Enhancement of local regions

As luminance is being normalized in the range [0 to 1], which is global compression operation which can be possibly reduce local contrast from some region, there an operator is used to recover details of an image as local contrast operator. In this work the Difference of Gaussian (DOG) is used to improve image details which are corrected in previous steps.

$$L'_B = L_B(x,y) + \left(L_B * DOG_{\sigma_c,\sigma_s}\right)(x,y) \tag{15}$$

$$L'_D = L_D(x,y) + \left(L_D * DOG_{\sigma_c,\sigma_s}\right)(x,y) \tag{16}$$

$$DOG_{\sigma_c,\sigma_s}(x,y) = \frac{1}{2\pi\sigma_c^2}\ exp\left(-\frac{x^2+y^2}{2\sigma_c^2}\right) - \frac{1}{2\pi\sigma_s^2} exp\left(-\frac{x^2+y^2}{2\sigma_s^2}\right) \tag{17}$$

where * denotes convolution operator. Here the $\sigma_c = 0.5$ and $\sigma_s = 3\sigma_c$ [30] for DoG filter.

Gamma correction to both the parts will give better contrast in dark part (L'_D) and will preserve details in bright part along with controlling over enhancement of over bright region (L'_B).

3.6. Adaptive fusion

To integrate gamma corrected images adaptive luminance dependant fusion method is used [30] as

$$L_{fused}(x,y) = wt(x,y). L'_D(x,y) + (1 - wt(x,y)). L'_B \tag{18}$$

where $wt(x,y)$ is a spatial varying weight used to balance the brightness levels of different portions of L'_B and L'_D.

$$wt(x,y) = exp\left(-\frac{L_B(x,y)^2}{2\sigma_{wt}^2}\right) \tag{19}$$

where σ_{wt} is considered as 0.5. L_{fused} image will finally enhance the details in both the regions.

3.7. Colour restoration

L_{fused} gives enhanced luminance part of an image. The next task is to restore original colours of an image. It is essential to add colour correction step for preserving details of colour appearance of an image because after compression of dynamic range, it usually causes colour shift (under-saturated and over-saturated). Many colour restoration methods are given by researchers in [35, 37, 38] but the easier and promising method to reduce the colour shift while combining luminance in colour image is by keeping a ratio at constant between colour channels after and before dynamic range adjustment. Eqs. (22)-(24) [30] depicts the final R, G and B components of an image,

$$I_R(x,y) = L_{fused}(x,y)\left(\frac{In_{image}(x,y)^R}{L_{norm}(x,y)}\right)^{s(x,y)} \tag{20}$$

$$I_G(x,y) = L_{fused}(x,y)\left(\frac{In_{image}(x,y)^G}{L_{norm}(x,y)}\right)^{s(x,y)} \tag{21}$$

$$I_B(x,y) = L_{fused}(x,y)\left(\frac{In_{image}(x,y)^B}{L_{norm}(x,y)}\right)^{s(x,y)} \tag{22}$$

$$s(x,y) = 1 - tanh\,(L_B(x,y)) \tag{23}$$

where exponent s is used to adjust the saturation of pixels for example by reducing exponent s the saturation of pixels with high brightness can be attenuated. This higher saturation in brightness of image will appear in dazzling. Also, to avoid excessive under saturation $tanh$ function is used.

Final enhanced output image of proposed method is obtained by concatenating R, G and B components given in Eqs. (20)-(22) as,

$$Out_{Image}(x,y) = I_R(x,y) + I_G(x,y) + I_B(x,y) \tag{24}$$

4. Results and Discussion

The results of the Existing method [30] (AMIDRA) enhancing low contrast images by considering a fixed value of threshold (threshold=0.5) which is independent of luminance of input low contrast image and based on which the luminance part of input image is divided into two parts bright and dark parts are shown in this section. Also, this section comprises of further experimentation done on the low contrast images in which the segregation of luminance component is done based on threshold which is dependant the luminance of low contrast images. Later the results obtained by using different colour spaces like YCbCr and Kekre's LUV colour space are shown. Hence the proposed method has two significant modifications in the existing method as (i) adaptive threshold computation which is based on luminance dependant of low contrast image (ii) changing colour space for betterment of results. Figure 2 shows the processing stepwise intermediate outputs of proposed Contrast Enhancement using Adaptive Threshold based Image Dynamic Range Adjustment in Kekre's LUV Colour Space.

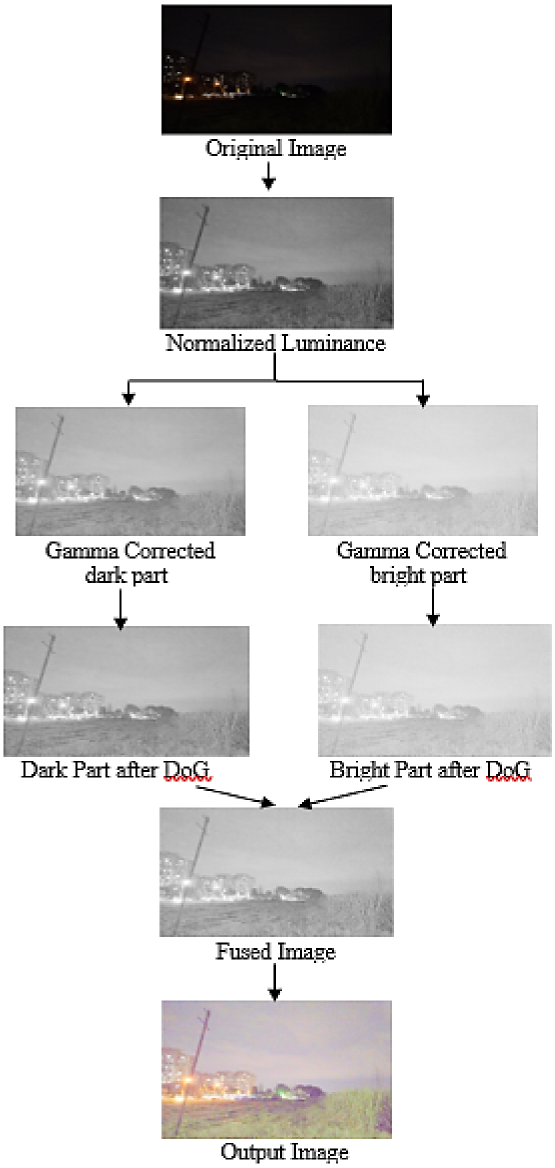

Fig. 2. Processing stepwise intermediate outputs of proposed contrast enhancement using adaptive threshold based image dynamic range adjustment in Kekre's LUV colour space.

A complete dataset of 30 night-time images used in this paper is shown in Fig. 3. These images are captured during night so that the original image is unable visualize by human eye and hardly see the objects present in it. Dataset contains images of buildings, roads, trees, water bodies, etc.

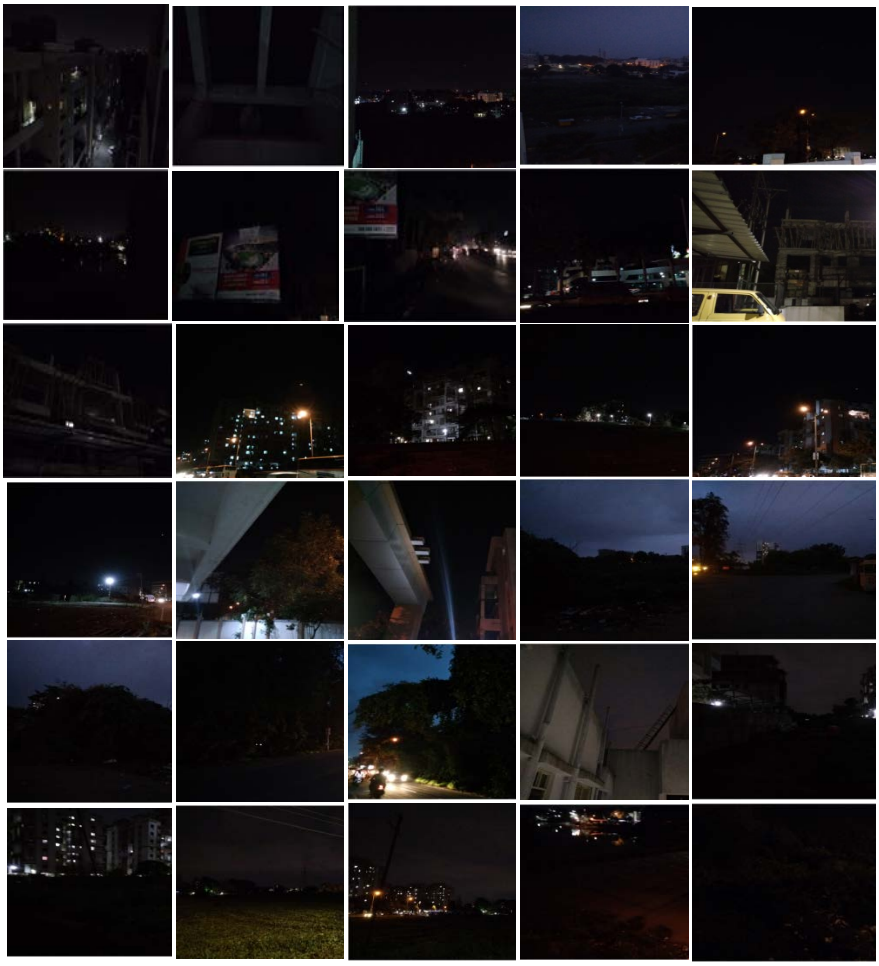

Fig. 3. Dataset of night-time images.

Here the existing contrast enhancement methods like Histogram Equalization (HE) [1], "Multi Scale Retinex with Colour Restoration" (MSRCR) [23] and "Adaptive Method for Image Dynamic Range Adjustment" (AMIDRA_0.5) are considered for comparison of the proposed "Adaptive Threshold based Image Dynamic Range Adjustment Method" (ATIDRA) and Adaptive Threshold based Image Dynamic Range Adjustment Method in Kekre's LUV colour space (LATIDRA).

AMIDRA limitations with HE and MSRCR

Figure 4 shows the contrast enhancement applied on two of the low contrast images using existing techniques alias HE [1], MSRCR [23] and AMIDRA [30]. Here HE [1] output shows over enhancement of brighter regions creating the colour bias and ringing effects as given in Fig. 4(b). In MSRCR [23] based contrast enhancement the naturalness of enhanced image is getting compromised due to the colour distortion introduced in contrast enhanced images as given in Fig. 4(c).

(a) Original low contrast image samples.

(b) Contrast enhancement done using HE [1].

(c) Contrast enhancement done using MSRCR [23].

(d) Contrast enhancement done using AMIDRA [30].

Fig. 4. Comparison of different existing methods of contrast enhancement.

The ATIDRA_0.5 [30] is not able to enhance the contrast of natural textures like leaves, water bodies etc. and the under enhancement of some of the darker regions as given in the Fig. 4(d), which leaves the scope of improvement further. The improvements done in AMIDRA by taking the adaptive luminance dependant threshold value are shown on Fig. 5. Here the variations of proposed ATIDRA (Adaptive Threshold based Image Dynamic Range Adjustment Method) are experimented on two the sample low contrast images. In ATIDRA the image luminance dependant adaptive threshold is computed as exposure (ATIDRA_ex), mean (ATIDRA_mn) and median (ATIDRA_md) values of normalized luminance of low contrast image as elaborated in Eqs. (3), (5) and (6) of Section 3.

In Fig. 5 the parts (a), (b), (c) and (d) respectively are showing results obtained by the existing AMIDRA [20] and proposed ATIDRA_ex (adaptive threshold as exposure), ATIDRA_mn (adaptive threshold as mean) and ATIDRA_md (adaptive threshold as median). Here it can be observed that the drawback of AMIDRA [30] based contrast enhancement in which under enhancement of darker regions is up to some extent taken care by ATIDRA_mn and ATIDRA_md c and d part of both examples in Fig. 5 but somehow ATIDRA_ex (part b of both the examples of Fig. 5 is not enhancing over AMIDRA [30] for this problem of under enhancement also the contrast enhancement of is observed to be relatively better in proposed ATIDRA_mn and ATIDRA_md as compared that done by existing AMIDRA [30].

The improvements are observed in proposed ATIDRA due to consideration of image luminance dependant threshold computation done as exposure (Eq. (6)), mean (Eq. (3)) and median (Eq. (5)) of the normalized luminance of low contrast image. These improvements are objectively compared using average NIQE (Naturalness Image Quality Evaluator) [47] and Entropy values computed for all 30 images considered in dataset (Fig. 4) as shown in Fig. 7. Naturalness image quality evaluator (NIQE) [47] and Entropy calculates the no-reference image quality score. NIQE measures the distance between the natural scene statistics (NSS) based feature set calculated from the considered image to those obtained from a corpus of images used to compute the model parameters. The NIQE score is a scalar value in the range [0, Infinity]. Lower values of NIQE score reflects better perceptual quality. Basically, Entropy is known as statistical measure of randomness which is used to characterize the textural part of the input image. Higher the entropy value better the image quality.

(i) Original image low contrast image.

(a) Contrast enhancement using AMIDRA [17].

(b) Contrast enhancement using proposed ATIDRA_ex.

(c) Contrast enhancement using ATIDRA_md.

(d) Contrast enhancement using ATIDRA_mn.

(ii) Original image low contrast image.

(a) Contrast enhancement using AMIDRA [17].

(b) Contrast enhancement using proposed ATIDRA_ex.

(c) Contrast enhancement using ATIDRA_md.

(d) Contrast enhancement using ATIDRA_mn.

Fig. 5. Exemplic results of contrast enhancement done in proposed AMIDRA with adaptive threshold as exposure (ATIDRA_ex), as median (ATIDRA_md) and as mean (ATIDRA_mn).

Here in Fig. 6 the proposed ATIDRA_mn has given better performance as indicated by lower average NIQE score in YCbCr colour space closely followed by ATIDRA_md as compared to existing AMIDRA [30] proving the worth of Adaptive threshold computation proposed here as ATIDRA (Adaptive Threshold based Image Dynamic Range Adjustment Method) and the least NIQE score is shown by LATIDRA_mn of Kekre's LUV colour space indicating that Kekre's LUV colour space has upper hand compared to YCbCr colour space. Also Fig. 7 shows the comparison of Entropy values of existing methods as well as proposed adaptive threshold methods. Here ATIDRA_md gives high entropy value in YCbCr colour space while the highest Entropy value amongst all is given by LATIDRA_md of Kekre's LUV colour space with close resemblance to LATIDRA_mn.

Figure 8 gives the performance comparison of few of existing popular contrast enhancement methods alias Histogram Equalization (HE) [1], Multi Scale Retinex with Colour Restoration (MSRCR) [23], Adaptive Method for Image Dynamic Range Adjustment (AMIDRA) [30] with proposed Adaptive Threshold based Image Dynamic Range Adjustment Method (ATIDRA) with threshold as exposure (ATIDRA_ex), threshold as mean (ATIDRA_mn) and threshold as median (ATIDRA_md) of normalized luminance 'Y' (Y of YCbCr colour space) as well as with the proposed ATIDRA with Kekre's LUV colour space based contrast enhancement (LATIDRA) with exposure, median and mean of normalized luminance 'L' (L of Kekre's LUV colour space) respectively referred as LATIDRA_ex, LATIDRA md and LATIDRA_mn. The sample low contrast images (as given in Fig. 8) are processed with all these contrast enhancement methods as original low contrast image (a, l), HE (b, m), MSRCR (c, n), AMIDRA (d, o), ATIDRA_ex (e, p), ATIDRA_md (f, q), ATIDRA_mn (g, r), LATIDRA_0.5 (h, s), LATIDRA_ ex (i, t), LATIDRA_md (j, u) and LATIDRA_mn (k, v) with respective NIQE score.

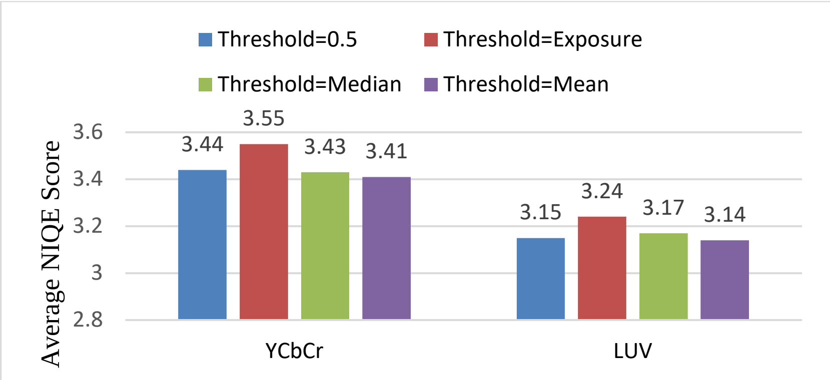

Fig. 6. Performance comparison of average NIQE score of existing AMIDRA [30] based contrast enhancement with variations of the proposed contrast enhancement method adaptive threshold based Image Dynamic Range Adjustment (ATIDRA) as ATIDRA_ex (threshold as exposure), ATIDRA_md (threshold as median) and ATIDRA_mn (threshold as mean) in YCbCr colour space and Kekre's LUV colour space based contrast enhancement LATIDRA (threshold as 0.5), LATIDRA_ex (threshold as exposure), LATIDRA_md (threshold as median) and LATIDRA_mn (threshold as mean).

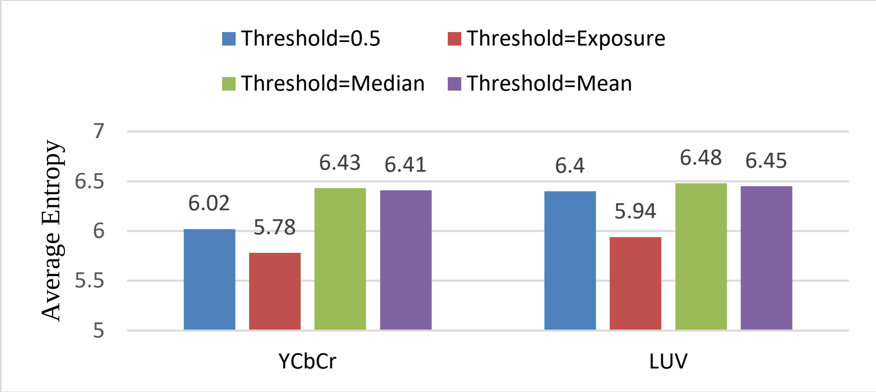

Fig. 7. Performance comparison of average Entropy of existing AMIDRA [30] based contrast enhancement with variations of the proposed contrast enhancement method adaptive threshold based Image Dynamic Range adjustment (ATIDRA) as ATIDRA_ex (threshold as exposure), ATIDRA_md (threshold as median) and ATIDRA_mn (threshold as mean) in YCbCr colour space and Kekre's LUV colour space based contrast enhancement LATIDRA threshold as 0.5), LATIDRA_ex (threshold as exposure), LATIDRA_md (threshold as median) and LATIDRA_mn (threshold as mean).

Here it can be easily observed that proposed ATIDRA gives better enhancement with 'ATIDRA_mn' variation over existing popular methods and best performance is observed in proposed 'LATIDRA_mn' method as indicated by lower NIQE scores. Figure 8 compares the threshold adaptations considered as constant (0.5), mean of normalized luminance of low contrast image (threshold=mean), median of normalized luminance of low contrast image (threshold=median) and exposure of normalized luminance of low contrast image (threshold=exposure) both in Kekre's LUV and YCbCr colour space.

Table 1 gives NIQE score and Entropy values obtained by taking average of all the 30 dataset images after contrast enhancement with the existing popular contrast enhancement methods as (HE, MSRCR and AMIDRA) and proposed contrast enhancement methods based on adaptive thresholds (as ATIDRA_ex, ATIDRA_mn and ATIDRA_md) as well as Kekre's LUV colour space-based Image Dynamic Range Adjustment (as LATIDRA_ex, LATIDRA_mn and LATIDRA_md). The table shows that proposed methods give better contrast enhancement as indicated by NIQE and Entropy scores as compared to existing well-known methods. The adaptive threshold computation based on normalized luminance 'Y' (Y in YCbCr colour space converted low contrast image) gives better contrast adjustment with mean as ATIDRA_mn. Also, the contrast adjustment further got better in threshold as mean as normalized luminance 'L' (L in Kekre's LUV colour space converted low contrast image) as indicated by lowest average NIQE score for LATIDRA_mn and highest entropy values for LATIDRA_md

(i) Original low contrast image.

(a) CE using, HE [1] NIQE=2.91.

(b) CE using MSRCR [23] NIQE=2.

(c) CE using AMIDRA [30] NIQE=2.09.

(d) CE using proposed ATIDRA_ex NIQE=2.11.

(e) CE using proposed ATIDRA_md NIQE=2.1.

(f) CE using proposed ATIDRA_mn NIQE=2.21.

(g) CE using proposed LATIDRA_0.5 NIQE=2.02.

(h) CE using proposed LATIDRA_ex NIQE=2.33.

(i) CE using proposed LATIDRA_md NIQE=2.03.

(j) CE using proposed LATIDRA_mn NIQE=2.13.

(ii) Original low contrast image.

(a) CE using, HE [1] NIQE=2.97.

(b) CE using MSRCR [23] NIQE=3.01.

(c) CE using AMIDRA [30] NIQE=2.63.

(d) CE using proposed ATIDRA_ex NIQE=2.92.

(e) CE using proposed ATIDRA_md NIQE=2.61.

(f) CE using proposed AMIDRA_mn NIQE=2.63.

(g) CE using proposed LATIDRA_0.5 NIQE=2.32.

(h) CE using proposed LATIDRA_ex NIQE=2.81.

(i) CE using proposed LATIDRA_md NIQE=2.42.

(j) CE using proposed LATIDRA_mn NIQE=2.32.

Fig. 8. Performance comparison of existing CE methods like HE [1], MSRCR [23], AMIDRA [30] with proposed ATIDRA_ex, ATIDRA_md, ATIDRA_mn, LATIDRA_0.5, LATIDRA_ex, LATIDRA_md and LATIDRA_mn.

The above results of NIQE are validated with t-Test for paired two sample for means and it is found that there is significant difference for HE [1] against proposed LATIDRA_mn, MSRCR [23] against proposed LATIDRA_mn and AMIDRA [30] against proposed LATIDRA_mn; as in all these comparisons the t. t Stat is greater than t Critical and p values are less than 0.05 as shown in Table 2.

Variation over other adaptive threshold considerations and better performance of Kekre's LUV colour space over YCbCr colour space. Finally, the observation that the 'mean' of normalized luminance of low contrast image in Kekre's LUV colour space to be considered as threshold in adaptive Image Dynamic Range adjustment proves to be better for contrast enhancement.

Table 1. Average NIQE and Entropy score of 30 low contrast images.

Contrast Enhancement Methods	NIQE	Entropy	Colour Space
HE [1]	3.85	5.94	RGB
MSRCR [23]	3.58	6.42	RGB
AMIDRA [30]	3.44	6.02	YCbCr
ATIDRA_ex	3.55	5.78	YCbCr
ATIDRA_md	3.43	6.44	YCbCr
ATIDRA_mn	3.41	6.41	YCbCr
LATIDRA_0.5	3.15	6.4	Kekre's LUV
LATIDRA_ex	3.24	5.94	Kekre's LUV
LATIDRA_md	3.17	6.48	Kekre's LUV
LATIDRA_mn	3.14	6.45	Kekre's LUV

Table 2. Validation of result using t-Test.

	HE [1] vs. LATIDRA_mn		MSRCR [23] vs. LATIDRA_mn		AMIDRA [30] vs. LATIDRA_mn	
Mean	3.853	3.14	3.58	3.14	3.44	3.14
Variance	0.9290	0.3647	0.3684	0.3647	0.4567	0.3647
t Stat	6.31		10.69		5.43	
P(T<=t) one-tail	0.00000034		0.000000000007		0.0000039	
t Critical one-tail	1.699		1.699		1.699	
P(T<=t) two-tail	0.00000068		0.000000000014		0.0000078	
t Critical two-tail	2.05		2.05		2.05	

5. Conclusions

This paper presents an effective contrast enhancement method for low contrast images captured during weak illumination conditions. Here the weak illumination image is divided in two parts using the threshold value taken as the parameter dependant on luminance of the low contrast image.

The proposed method considers the adaptive computation of threshold value as exposure, median and mean (instead of constant value 0.5 considered in earlier literature) of normalized luminance of low contrast image. The testbed of thirty weak illumination images is considered for experimentation. NIQE (Naturalness image Quality Evaluator) and Entropy are used as no reference image quality evaluation parameter.

The proposed contrast adjustment methods give better results because of the adaptive threshold computation as observed from experimentation carried out resulting in lower NIQE scores threshold=mean) and higher Entropy values (threshold=median) when Kekre's LUV colour space is considered in place of YCbCr colour space.

Note that as existing methods do not focus on enhancement of natural textures like leaves of tree, water bodies etc. which are properly highlighted in proposed enhancement methods by using adaptive threshold and Kekre's LUV colour space.

6. Future Scope

Though the proposed contrast enhancement method is giving better performance with Kekre's LUV colour space for nighttime images further it would be interesting to check the performance of the proposed contrast enhancement method with other low contrast images like very bright images (with very high illumination) and images with uneven contrast (uneven illumination). Also, the effect of using proposed contrast enhancement method as hybrid with other contrast enhancement techniques would be good exploration for future work.

Nomenclatures

B_{part}	Bright part of image
D_{part}	Dark part of image
I_B	Blue component of image I
I_G	Green component of image I
I_R	Red component of image I
$ia_{thr_{exposu}}$	Exposure as threshold
$ia_{thr_{mean}}$	Mean as threshold
$ia_{thr_{media}}$	Median as threshold
L_B	Luminance of bright part
L'_B	Gamma corrected luminance of bright part
L_D	Luminance of dark part
L'_D	Gamma corrected luminance of dark part
L_{fused}	Luminance of fused image
L_{norm}	Normalized luminance
In_{Image}	Input image
Med_H	Expected median of bright part
Med_L	Expected median of dark part
Out_{Image}	Output image
s	Saturation parameter
$wt(x, y)$	Spatial varying weight

Greek Symbols

γ	Gamma
γ_B	Gamma of bright part
γ_D	Gamma of dark part

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