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Image illumination enhancement with an objective no-reference measure of illumination assessment based on Gaussian distribution mapping

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A B S T R A C T

Illumination problems have been an important concern in many image processing applications. The pattern of the histogram on an image introduces meaningful features; hence within the process of illumination enhancement, it is important not to destroy such information. In this paper we propose a method to enhance image illumination using Gaussian distribution mapping which also keeps the information laid on the pattern of the histogram on the original image. First a Gaussian distribution based on the mean and standard deviation of the input image will be calculated. Simultaneously a Gaussian distribution with the desired mean and standard deviation will be calculated. Then a cumulative distribution function of each of the Gaussian distributions will be calculated and used in order to map the old pixel value onto the new pixel value. Another important issue in the field of illumination enhancement is absence of a quantitative measure for the assessment of the illumination of an image. In this research work, a quantitative measure indicating the illumination state, i.e. contrast level and brightness of an image, is also proposed. The measure utilizes the estimated Gaussian distribution of the input image and the Kullback-Leibler Divergence (KLD) between the estimated Gaussian and the desired Gaussian distributions to calculate the quantitative measure. The experimental results show the effectiveness and the reliability of the proposed illumination enhancement technique, as well as the proposed illumination assessment measure over conventional and state-of-the-art techniques.
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1. Introduction

Contrast enhancement is frequently referred to as one of the most important issues in image processing [1–3]. The difference in visual properties makes an object distinguishable from other objects and the background. The information may be lost in areas where contrast is highly concentrated on a specific range. The problem is to optimize the contrast of an image in order to represent all the information in the input image. There have been several techniques to overcome the problem [4–9]. One of the most frequently used techniques is general histogram equalization (GHE) [10,11]. Later enhanced versions of GHE, such as local histogram equalization (LHE), were developed. However, the contrast issue remains, and recently many techniques for image equalization have been proposed, such as dynamic histogram equalization (DHE) [12] which improves image illumination by using histogram equalization on very specific partitions of the histogram, brightness preserving dynamic histogram equalization (BP-DHE) [13,14] which normalizes the brightness of the image in order to preserve the brightness of the input image in the output, singular value equalization (SVE) which enhances the illumination of an image by updating the largest singular value of the given image, and discrete wavelet transform (DWT) based SVE [15–17] which updates the

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largest singular value of the low–low subband of an image based on the corresponding singular value on the image after being equalized by using histogram equalization. In addition to the contrast issue, there are many algorithms aimed at improving illumination in specific regions of the image. There are several types of problems for which these algorithms are proposed, such as if an image is unevenly illuminated (e.g. a portion of the image is in dark shadow) and another portion is in overly bright sunlight, then we usually want to improve the contrast in both parts of the image without creating an unnatural result [1,18–20].

There are several instances where due to different environmental factors it's not always possible to get a suitably illuminated image. For example, machine learning and object recognition techniques may lose their effectiveness if the illumination of the images changes due to the cloudiness of the sky [21–23].

In this work, a Gaussian distribution (GD) mapping-based image illumination enhancement is proposed. The aim of the proposed technique is to map the cumulative distribution function (CDF) of the GD of the input image onto the CDF of a desired GD in order to calculate the new pixel values of the enhanced image. The proposed illumination enhancement technique can be used as a pre-processing step for many other algorithms in order to improve their final results.

When analysing illumination methods other than visual analysis evaluation (i.e. subjective evaluation), there is no objective quantitative method to assess the illumination of the enhanced images. Some researchers use the mean opinion scores (MOS) in order to compare different illumination techniques; however, MOS is a subjective metric. Other image quality metrics, like the Face Quality Index, combine different properties (e.g. contrast, brightness, sharpness, illumination) of an image to achieve a metric used specifically in face recognition [24]. There is also a Universal Quality Index (UQI) that performs well if image distortion is being analysed [25]. Another common approach is to use a peak signal-to-noise ratio (PSNR) to assess the quality of an image. Using PSNR might be a good approach for a consistent, fixed content signal, but when applied to images or videos, it gives incomparable results across multiple contents [26]. Also it is important to note that in the case of illumination enhancement assessment, the absence of the ground truth limits the use of some the aforementioned techniques. There exist measures that try to deal with no-reference (NR) quality measurement. These approaches use machine learning techniques such as sparse extreme learning machine and neural networks [27–29]. They are based on the human visual system and try to emulate the MOS. Among other NR image quality assessment measures, methods have been developed to measure blur [30] and even colour harmony [31], but as yet not the illumination quality. In this paper we define a notation of an ideally illuminated image that will be the reference point for our metric. This does not fix one specific image but rather describes the properties that a mathematically ideal image should have.

We are proposing a new quantitative measure for image illumination quality which is based on finding the Kullback-Leibler Divergence (KLD) between an estimated Gaussian distribution of a given image and the desired Gaussian distribution. The desired Gaussian distribution can be chosen in a way that satisfies all the required and necessary features of an ideal enhanced image. The proposed metric generates a numerical value between −1 and 1 to reflect the quantitative assessment of illumination of a given image without using a ground truth image. A positive numeric value represents a high contrast image, and the negative value corresponds to a low contrast image. If the numeric value is in the (−0.5, 0.5) range, then the image is a dark image; otherwise it is a bright image. By using the proposed metric, all four possible image illumination quality cases (namely: low contrast-dark, low contrast-bright, high contrast-dark and high contrast-bright) can be represented.

Section II introduces the proposed image illumination enhancement technique based on GD mapping. In Section III the proposed image illumination assessment measure that is used to assess the illumination of an image is introduced. Section IV presents experimental results obtained using the image illumination enhancement technique and analyses their illumination state with the proposed measure.

2. Proposed Gaussian distribution mapping based image illumination technique

The main aim of this illumination enhancement is to change the brightness and contrast of an image into "better" or "desired" brightness and contrast. The "desired" brightness and/or contrast are defined based on the application by the users or experts. In the proposed technique, there exist two parallel stages:

1. Based on the application, the mean and variance of "desired" brightness and contrast should be defined. Brightness is addressed by indicating the mean, μ_d, of the intensity image, and contrast is addressed by indicating the variance, σ_d^2, of the intensity image. After specifying the μ_d and σ_d^2, a Gaussian distribution (GD) will be assigned to this "desired" illumination by using the following equation:

$$G_d\left(\mu_d, \sigma_d^2\right)(x) = \frac{1}{\sqrt{2\pi\sigma_d}} e^{-\frac{(x-\mu_d)^2}{2\sigma_d^2}} \quad (1)$$

where $x \in [0,255]$ for an 8-bit grey scale image. Then the cumulative distribution function (CDF) of this GD is calculated, as shown in eqn. (2).

$$CDF_{GD}(x) = \frac{1}{2}\left[1 + \frac{1}{\sqrt{\pi}} \int_{-\frac{x-\mu}{\sqrt{2}\sigma}}^{\frac{x-\mu}{\sqrt{2}\sigma}} e^{-t^2} dt\right] \quad (2)$$

2. In parallel, the mean, μ_{im}, and variance, σ_{im}^2, of the input image is calculated, and the GD assigned to these values is generated by using the general formula shown in eqn. (1). Similarly the CDF of this GD is also calculated.

These two steps are used to produce mapping of the image pixel values onto the new equalized values. For this purpose, the following procedure is followed:

1. Calculate the CDF value of a given intensity pixel value from the CDF_{im}.
2. Find the intensity pixel value that corresponds to the CDF value calculated in step 1 on CDF_d.

Using the aforementioned mapping procedure, a new table of pixel values will be generated. This table will be used in order to obtain the enhanced image. The graphical representation of the proposed technique is illustrated in Fig. 1. In the next section, based on the definition of desired GD, G_d, and image's GD, G_{im}, a measure will be introduce which can be used for illumination assessment.

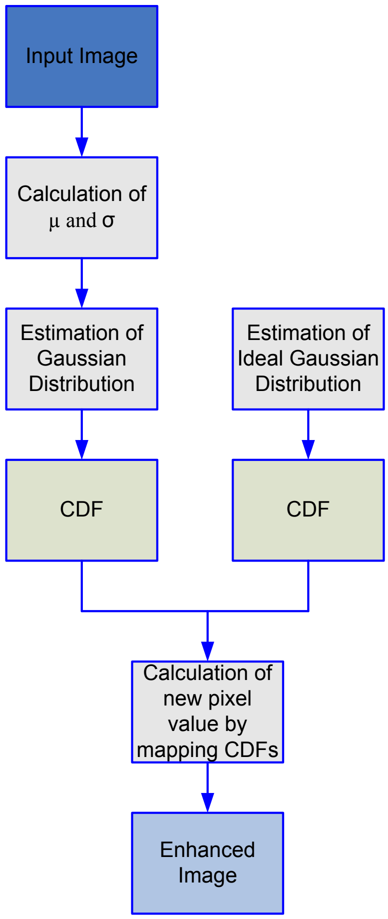


Fig. 1. Flowchart describing the proposed image illumination enhancement technique.

3. Image illumination assessment measure

Many quality measurement methods, such as the PSNR and UQI calculations, require a ground truth image, but it would be useful to have a technique that did not have this requirement. This is the main motivation for introducing a measure which can be used to assess the illumination quality independent of the ground truth image. The proposed measure is based on statistical pixel intensity distributions of the given image and the so called ideal/desired image. The main problem in a ground truth image independent approach is the identification of the desired statistical pixel intensity distribution in a desired image. Each pixel of an image can be considered as a random variable, and any image can be considered to be a combination of many random variables. According to the Central Limit Theorem [24], the addition of infinitely many distributions will be a GD. With a good approximation, an image is a combination of many pixels, i.e. random variables. Hence, the distribution of an ideally good illuminated image can be considered as the addition of many distributions, which will be a GD. Therefore, we can consider that the GD of an image with the desired illumination, has a mean of 128 ($\mu = 128$) for an 8-bit grey scale image. The standard deviation (σ) of the desired distribution should be calculated in order to estimate the GD of a desired image. An 8-bit grey level image has the pixel range of [0, 255]. Hence, the σ should be calculated in such a way that the GD covers this range effectively. It is known that the following transformation is valid:

$$X = \mathrm{G}\left(\mu, \sigma^2\right) \xrightarrow{z = \frac{x-\mu}{\sigma}} Z = \mathrm{N}(0, 1) \tag{3}$$

where N is representing a normal distribution. Assume that we want our estimated distribution to satisfy the following condition:

$$P(0 \le x \le 255) = 0.998 \tag{4}$$

Given that $\mu = 128$, in order to find σ, one can easily follow the proceeding steps:

$$\begin{aligned} &P(0 \le x \le 255) = 0.998 \\ &P(-Z_0 \le z \le Z_0) = 0.998 \\ &P(0 \le z \le Z_0) = \frac{0.998}{2} = 0.499 \end{aligned} \tag{5}$$

By using the table of Normal curve areas, we get:

$$\begin{aligned} &Z_0 = 3.09 \\ &Z_0 = \frac{255-128}{\sigma} \rightarrow \sigma = \frac{255-128}{3.09} \approx 41.1003 \end{aligned} \tag{6}$$

This calculation also holds for other probability values given in eqn. (6). Table 1 shows different values of σ obtained by the procedure in eqn. (6) for different probabilities.

Therefore a GD with a mean of 128 and a standard deviation of 41.1003, $\mathrm{G}_d\,(\mu = 128, \sigma^2 = 1689.2347)$, can be considered as a desired distribution. In addition for a given image (which can be an output of any illumination enhancement technique), the estimated GD of such an image, G_{im}, can be calculated by using eqn. (1). It is important to note that G_{im} is an estimated Gaussian distribution of the image based on its mean and standard deviation and G_{im} is not necessarily indicating the actual distribution of the image.

In order to proceed, it is important to note that the resulting GDs have been scaled in such a way that they have a peak value of 1 by using the following formula:

$$\mathrm{G}_{im}\left(\mu_{im}, \sigma_{im}^2\right)(x) = \frac{\mathrm{G}_{im}\left(\mu_{im}, \sigma_{im}^2\right)(x)}{\max\limits_{x} \mathrm{G}_{im}\left(\mu_{im}, \sigma_{im}^2\right)(x)} \tag{7}$$

Now we can find the divergence between the estimated scaled GD of the input image, G_{im}, and the desired scaled GD, G_d by using KLD. The lower this value, the better the illumination because it represents how similar G_{im} to G_d is. This value, κ, can be formulated as follows:

$$\kappa(G_{im}, G_d) = \sum_{j=0}^{255} G_{im_j} \cdot \log\left(\frac{G_{im_j}}{G_{d_j}}\right) \tag{8}$$

where variable j represents the possible grey level range which is [0, 255]. Hence there is no need to include the $(-\infty,-1]\cup[256,\infty)$. In

Table 1
Desired standard deviations for different probabilities.

$P(0 \le x \le 255)$	Z_0	σ
0.998	3.09	41.1003
0.990	2.33	54.5064
0.950	1.64	77.4390
0.900	1.29	98.4496
0.850	1.04	122.1154
0.800	0.84	151.1905
0.500	0.00	–

order to avoid any division by 0 or logarithm of 0, we can modify the eqn. (8) into the following form:

$$\kappa(G_{im}, G_d) = \sum_{j=0}^{255} G_{im_j} \cdot \log\left(\frac{G_{im_j} + \varepsilon}{G_{d_j} + \varepsilon}\right) \tag{9}$$

where ε is a very small number (e.g. 10^{-6}).

In order to normalize κ, the divergence value should be divided by its maximum possible value. The maximum distance occurs when we have an impulse on one of the grey levels with the peak value equal to $\sum G_d$, e.g. δ_b ($j = 0$) or δ_w ($j = 255$). Let assume that this maximum KLD value is shown by κ_{max}, which is as follows:

$$\kappa_{max} = \sum_{j=0}^{255} \delta_w \cdot \log\left(\frac{\delta_w + \varepsilon}{\delta_{d_j} + \varepsilon}\right) \tag{10}$$

Therefore the normalized divergence can be calculated by

$$\overline{\kappa}(G_{im}, G_d) = \frac{\kappa(G_{im}, G_d)}{\kappa_{max}} \tag{11}$$

It holds that $\overline{\kappa} \in [0, 1]$. When $\overline{\kappa}$ is equal to 0, it means we have the perfect match between the G_{im} and G_d scaled distributions, which means that the input image has the ideal/desired illumination. Let's define ξ to be the illumination metric that would generate a similarity measurement of the estimated scaled GD of the input image, and the desired scaled Gaussian distribution, which has a value between 0 and 1. ξ can be formulated by modifying eqn. (10) as follows:

$$\begin{aligned}\xi(G_{im}, G_d) &= sign(\mu_{im} - 128)\left|\frac{1}{2}\overline{\kappa}\right| + 0.5 \\ &= sign(\mu_{im} - 128)\left|\frac{\kappa(G_{im}, G_d)}{2 \cdot \kappa_{max}}\right| + 0.5\end{aligned} \tag{12}$$

From eqs. (9), (10) and (12) it follows that:

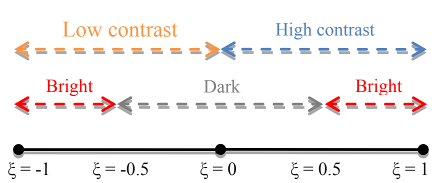


Fig. 2. ξ value guideline for determining illumination state.

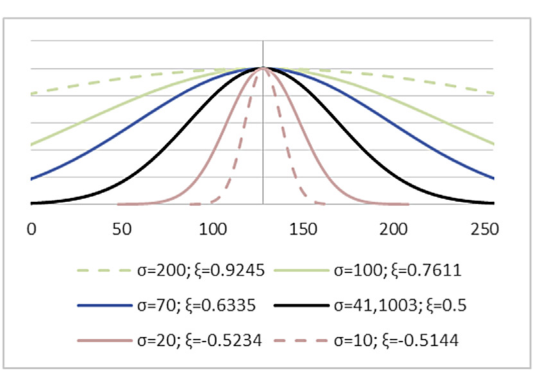


Fig. 3. Different normalized GD values with mean 128, where x-axis shows the x values in eqn. (1).

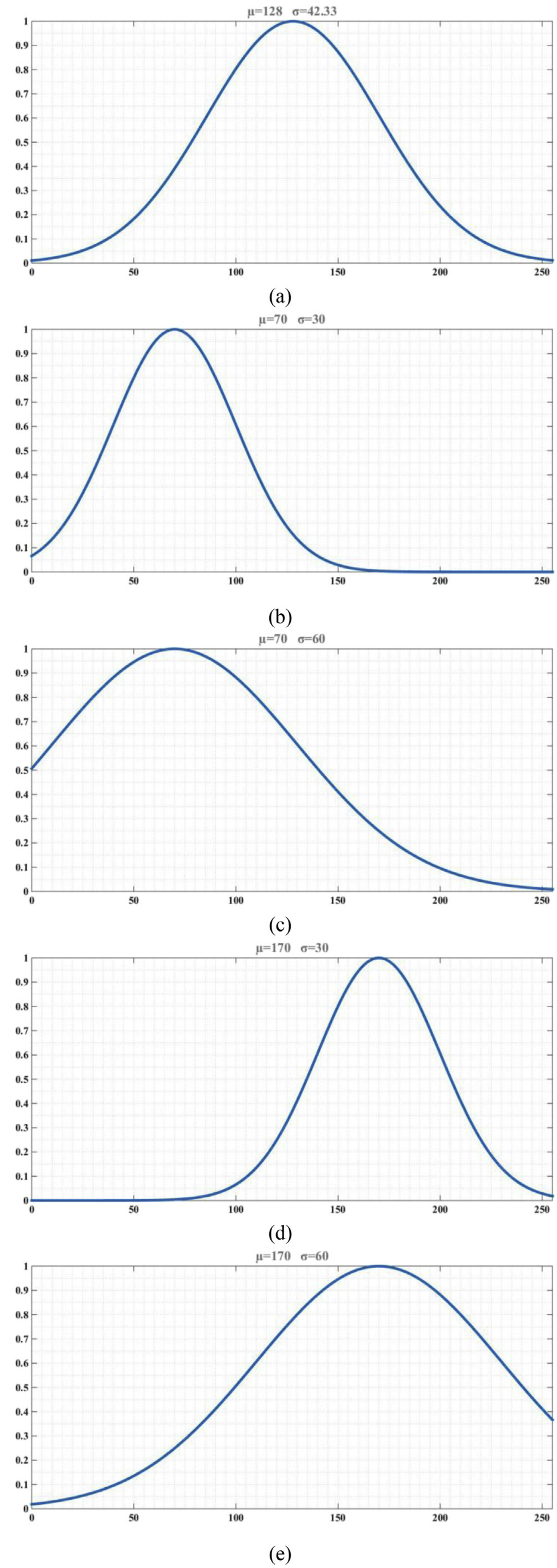


Fig. 4. Scaled GD of: a near-ideal image (a), a dark, low-contrast image (b), a dark, high-contrast image (c), a bright, low-contrast image (d), and a bright, high-contrast image (e), where x-axis is the x values in eqn. (1).

$$\xi(G_{im},G_d) = sign(\mu_{im}-128)\left|\frac{\sum_{j=0}^{255} G_{im_j}\cdot\log\left(\frac{G_{im_j}+\varepsilon}{G_{d_j}+\varepsilon}\right)}{2\cdot\sum_{j=0}^{255}\delta_w\cdot\log\left(\frac{\delta_w+\varepsilon}{G_{d_j}+\varepsilon}\right)}\right| + 0.5 \tag{13}$$

The function *sign* used in eqs. (12) and (13) is defined as:

$$sign(x) = \begin{cases} 1 & x \ge 0 \\ -1 & x < 0 \end{cases} \tag{14}$$

Introducing the *sign* function helps to differentiate the input image into dark and bright images. An image with $0 \le \xi < 0.5$ represents a dark image, and an image with $0.5 < \xi \le 1$ represents a bright image.

In order to enrich the eqn. (13) so that the result can also give some idea about the contrast of the distribution of the image (i.e. the image has a low or high contrast), variance of the distribution will be taken into the account. Hence considering all these issues, we modify the eqn. (13) and propose the following metric for illumination quality:

$$\begin{aligned}\xi(G_{im},G_d) =& sign(\sigma_{im}-41.1003)\\ &\times\left[sign(\mu_{im}-128)\left|\frac{\sum_{j=0}^{255} G_{im_j}\cdot\log\left(\frac{G_{im_j}+\varepsilon}{G_{d_j}+\varepsilon}\right)}{2\cdot\sum_{j=0}^{255}\delta_w\cdot\log\left(\frac{\delta_w+\varepsilon}{G_{d_j}+\varepsilon}\right)}\right| + 0.5\right]\end{aligned} \tag{15}$$

where $-1 \le \xi \le 1$ and $\xi_{\text{ideally illuminated image}} = 0.5$. In its final form, the sign of ξ indicates the contrast of the image. If ξ is a positive number, it means that the image has a high contrast, and if it is a

Table 2
Proposed measure values and their analysis for different estimated distributions.

Estimated distribution	ξ	Illumination analysis
$G(128, 42.33^2)$	0.5038	Close to ideally illuminated image
$G(70, 30^2)$	−0.4318	Dark image with low contrast
$G(70, 60^2)$	0.3490	Dark image with high contrast
$G(170, 30^2)$	−0.5264	Bright image with low contrast
$G(170, 60^2)$	0.6221	Bright image with high contrast

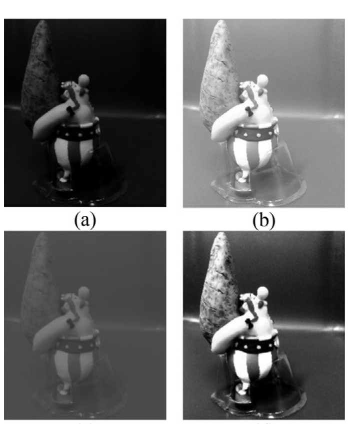


Fig. 5. Original images: dark image (a), bright image (b), low contrast image(c), and high contrast image(d).

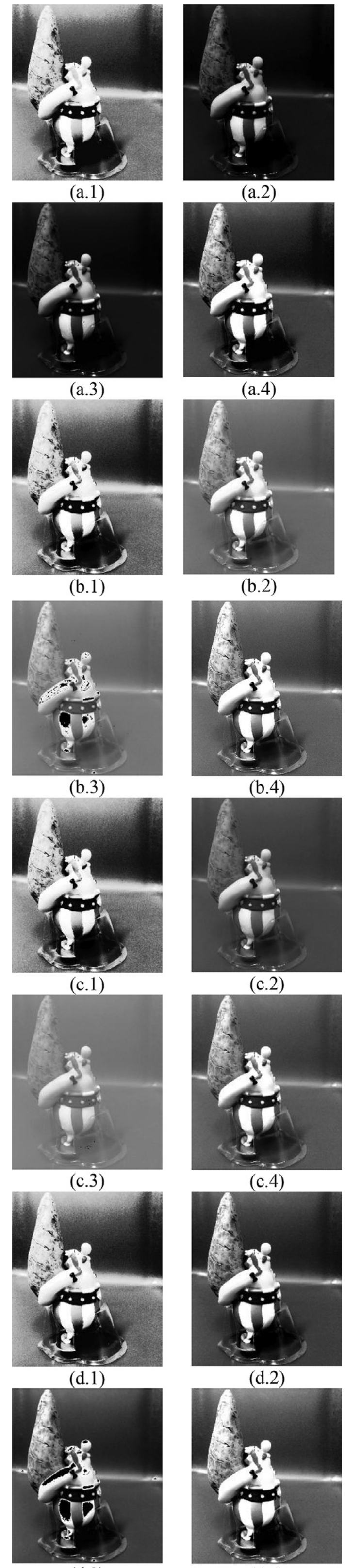


Fig. 6. Comparison of different illumination enhancement techniques: GHE (a–d.1), SVE (a–d.2), LHE (a–d.3), and the proposed illumination enhancement technique (a–d.4).

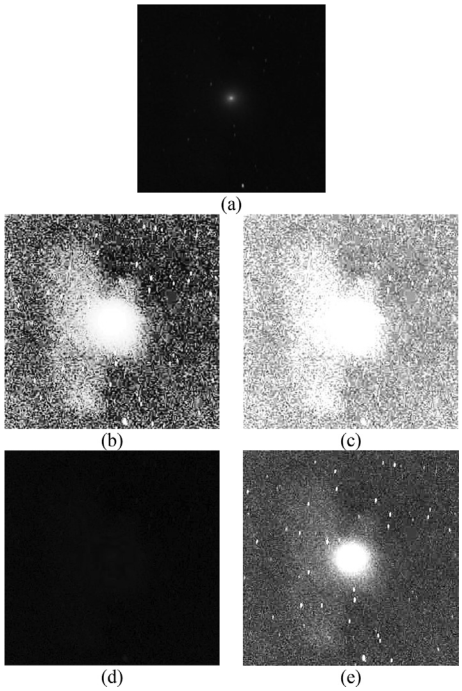
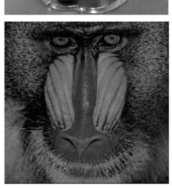
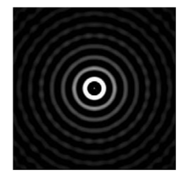
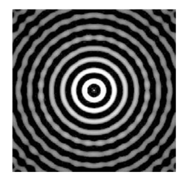
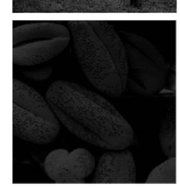
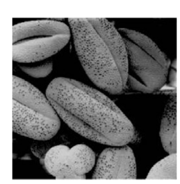


Fig. 7. Comparison of different illumination enhancement techniques: original input image (a), GHE (b), SVE (c), BP-DHE (d), and the proposed illumination enhancement technique (e).

Table 3
Experimental results prior to and after image enhancement.

	Image	μ	σ	ξ
Prior to enhancement		167.96	28.61	−0.5082
After enhancement		121.50	54.42	0.4936
Prior to enhancement		64.05	36.33	−0.4817
After enhancement		120.88	68.09	0.4856
Prior to enhancement		9.30	6.37	−0.4326
After enhancement		120.71	39.26	−0.4967
Prior to enhancement		17.87	34.29	−0.4759
After enhancement		70.78	74.59	0.4785
Prior to enhancement		28.67	44.54	0.4786
After enhancement		71.66	70.97	0.4797
Prior to enhancement		17.98	24.74	−0.4818
After enhancement		85.63	67.34	0.4826

negative number, then it indicates that the image has a low contrast as shown in Fig. 2.

Fig. 3 illustrates several distributions with $\mu = 128$, different standard deviations (σ), and respective ξ values for low contrast and high contrast images with the same mean. An ideal image would have ξ to be 0.5, which is stated in eqn. (15). As the figure shows

Table 4
Illumination state assigned on an average to the images.

Illumination state of the provided image		Decision			
		Bright	Dark	Low contrast	High contrast
Bright	Decision based on average ξ value (%)	100	0		
	Decision based on average MOS (%)	100	0		
Dark	Decision based on average ξ value (%)	0	100		
	Decision based on average MOS (%)	0	100		
Low contrast	Decision based on average ξ value (%)			100	0
	Decision based on average MOS (%)			96	4
High contrast	Decision based on average ξ value (%)			0	100
	Decision based on average MOS (%)			17	83

Table 5
Quality ranking on Fig. 6 by the MOS and the proposed measure.

		GHE	SVE	LHE	Proposed technique
Fig. 6a	ξ value	0.4819	0.4789	−0.4749	**0.4835**
	Average MOS ranking	2	3	4	**1**
Fig. 6b	ξ value	0.4818	**−0.5022**	−.05184	0.4936
	Average MOS ranking	3	**1**	4	2
Fig. 6c	ξ value	0.4899	−0.5008	−0.4895	**0.4993**
	Average MOS ranking	3	2	4	**1**
Fig. 6d	ξ value	0.4818	0.4859	0.4567	**0.4880**
	Average MOS ranking	3	2	4	**1**

Bold values show which method perform better.

Gaussian distributions with different \sigma values, hence x-axis is the value of parameter x in Gaussian distribution equation (eqn. (1)) and y-axis the Gaussian value obtained by the same formula. In order to demonstrate the effect of changing of σ, Gaussian distribution values have been normalized so that all with have a peak at $\mu = 128$.

Consider the five distributions in Fig. 4. By using eqn. (15), the respective ξ values of Fig. 4 can be calculated. Table 2 shows the calculated measure (ξ) values. According to these values, Fig. 4 (a) shows an estimated GD of approximately an ideally illuminated image. Fig. 4 (b–c) shows an estimated GD of two dark images with low and high contrasts respectively. Also, Fig. 4 (d–e) illustrates an estimated GD of two bright images with low and high contrasts respectively.

4. Experimental results

The qualitative and quantitative comparison has been conducted for the proposed GD mapping-based illumination enhancement technique. Figs. 5 and 6 illustrate a visual comparison of our image illumination technique with GHE, SVE and LHE. Fig. 7 shows the qualitative representation of the proposed illumination enhancement technique compared with GHE, SVE, and BP-DHE. Also a couple of images and the measure values for those, prior to and after applying the proposed illumination enhancement technique, are presented in Table 3.

It can be seen from the results that the proposed GD mapping-based image illumination enhancement technique outperforms the other conventional and state-of-the-art-techniques. In order to verify the effectiveness of the proposed measure, a mean opinion score (MOS) has also been studied. The MOS analysis has been done by asking 75 randomly selected students at both the University of Tartu and Eastern Mediterranean University to vote for 36 images with different illumination states namely, 9 dark images, 9 bright images, 9 low contrast images, and 9 high contrast images. Also the ξ value for each of these images has been calculated by using eqn. (15), and then the illumination state of the images has been assigned by using guideline shown in Fig. 2. Table 4 shows the results of the MOS and the proposed measure.

As it is shown in Table 4, the proposed measure is very effective in determining the illumination state of a given image. Also the images in Fig. 6 were shown to the same set of students who were asked to sort them based on the visual quality where 1 represents the best and 4 represents the worst. Table 5 shows the MOS result of ranking as well as the calculated ξ values (the given ideal mean = 128 and the ideal standard deviation is 41.1003). Knowing that $\xi = 0.5$ is an image with ideal illumination, the proposed measure is in line with the MOS; hence it can be used to compare illumination enhancement techniques quantitatively.

5. Conclusion

This paper proposed an innovative approach for image-illumination enhancement by means of GD mapping. The underlying notion was to map the cumulative distribution function of the GD of the input image onto that of the image bearing the intended statistical property, which, as one of its virtues, could maintain the extreme values included in the original. Besides, in order to quantitatively evaluate the performance of the proposed methodology, and to compare its competence with that of other strategies suggested in the existing literature, an image-illumination index was introduced. Finally, the results of the implementation of the aforementioned technique on a bunch of benchmark images were presented, both quantitatively and qualitatively, which verified that it considerably outperforms relevant image-illumination enhancement methods.

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