Relighting Backlight and Spotlight Images using the von Kries Model

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Abstract: Improving the quality of backlight and spotlight images is a challenging task. Indeed, these pictures include both very bright and very dark regions with unreadable content and details. Restoring the visibility in these regions has to be performed without over-enhancing the bright regions, thus without generating unpleasant artifacts. To this end, some algorithms segment the image in bright and dark regions, re-work them separately by different enhancing functions. Other algorithms process the input image at multiple scales or with different enhancement techniques. All these methods merge the results together paying attention to the edge areas. The present work proposes a novel approach, called REK and implementing a relighting technique based on the von Kries model. REK linearly increases the channel intensities of the input image, obtaining a new brighter image, which is then summed up to the input one with weights computed from the input image and taking high values on the dark regions while low values on the bright ones. In this way, REK improves the quality of backlight and spotlight pictures without needing for segmentation and multiple analysis, while granting satisfactory performance at a computational complexity proportional to the number of image pixels.

1 INTRODUCTION

Good lighting is essential for capturing clear pictures. Unfortunately, in some contexts, such important condition is hard to meet. This is the case of environments with low light, backlight and spotlight. Under low light, the acquired scene appears entirely dark, while under backlight and spotlight the scene contains both very bright and very dark regions. Precisely, in the images with backlight, a foreground object is displayed against a very brilliant background, while in the images with spotlight, the light source, which is intense but not diffuse, is inside the acquired scene and produces a very bright region, while the rest is nearby black. In all these pictures, the content and the details of the scene are unreadable and algorithms for improving the quality of the dark areas are needed. While several algorithms exist for low-light images, e.g. (Lee et al., 2015), (Guo et al., 2017), (Lv et al., 2018), (Kwok et al., 2018), (Wang et al., 2020), (Li et al., 2020), (Wei et al., 2018), (Jiang et al., 2021), (Guo et al., 2022), there are only few works on the enhancement of backlight and spotlight images. The main issue with these images is that the dark areas must be reworked to increase their visual quality without over-enhancing the bright ones. Some algorithms, specifically designed for this task, segment the input image in dark and bright region and enhance them independently by different functions, e.g. (Ramirez Rivera et al., 2012), (Li and Wu, 2018). The enhanced regions are then merged together and the edge areas are usually post-processed to prevent the formation of undesired halos or artifacts. The use of different enhancement functions for dark and bright areas ensures in general good results, that however strongly depend on the segmentation. Multiscale Retinex approaches propose a different solution, not needing for segmentation, e.g. (Petro et al., 2014), (Morel et al., 2010), (Jobson et al., 1997). These algorithms process the input image at multiple resolutions. At each scale, the intensity of each pixel x is mapped onto a new value based on the spatial distribution of a set of colors sampled around x. The results obtained at the various scales are averaged together, returning an image where the details are preserved in the bright regions and magnified in the dark ones. Nevertheless, the output image often presents halos around the edges and the computational time of such algorithms is usually high. A recent Retinex inspired bilateral filter for backlight and spotlight image enhancement has been presented in (Lecca, 2021). This filter rescales the color intensity of each pixel by a value depending both on spatial and intensity features of some pix-

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els regularly sampled over the image. The algorithm performs well, but in some cases the output images appear washed out. Another approach is proposed in (Wang et al., 2016), where three different enhanced images are computed from the input one: in the first image, the dark areas are over-enhanced, in the second one the dynamic range of the bright regions is compressed, while in the third one the contrast is improved. The three images are smoothed by a Laplacian operator to remove noise and halos, then they are averaged together with weights controlling the overall brightness of the images. The results are generally satisfactory, but in some cases the dark regions are still quite dark.

The present work proposes a new algorithm, which relights the dark areas of backlight and spotlight regions without over-enhancing the bright ones and without needing for segmentation and/or multiple scale analysis. Relighting is performed based on the von Kries model (Finlayson et al., 1994), (Lecca, 2014), i.e. by rescaling the channel intensities of the input image by a factor α greater than 1, so that the brightness of the dark areas increases. This relighted image is summed up to the input one with weights depending on the input brightness and having high (low, resp.) values on the dark (bright, resp.) regions. This combination of images increases the visibility of content and details of the dark areas, while preserves the appearance of the bright areas. The parameter α is tunable by the user, but here an unsupervised estimation of α is also presented. The proposed algorithm, called REK from the keywords *RE*light and von *K*ries, has been tested on different backlight and spotlight images, showing good performance also in comparison with other state-of-the-art methods.

2 THE PROPOSED METHOD

The original von Kries model, presented in (Kries, 1905), provides a description of the human chromatic adaptation, which is the mechanism regulating the responses of the human vision system to varying viewing conditions, such as illumination. This adaptation is strictly related to the color constancy, i.e. to the human capability to discount light effects from the observed scene (Hirakawa and Parks, 2005). In computer vision, the von Kries model has been adapted to describe how the colors of a digital image changes when the illumination under which the image is acquired changes. Specifically, this model approximates such a change by a linear diagonal transform of the RGB triplets (Finlayson et al., 1993). In image processing, this transform has been widely employed for correcting color shifts of an image with respect to a reference one, showing very good performance (Berens and Finlayson, 2000), (Lecca and Messelodi, 2011), (Lecca, 2014).

Mathematically, let I be a color image and let I_0, I_1, I_2 be its color channels. Let x denote a pixel of I, and let B be the brightness of I, i.e. the gray-level image computed from I by averaging pixel-wise its three color channels, i.e.:

$$B(x) = \frac{1}{3}\sum_{i=0}^{2} I_i(x). \tag{1}$$

The von Kries model states that any change of light determines a rescaling of the values $I_0(x), I_1(x), I_2(x)$, i.e. for any i = 0, 1, 2:

$$I_i(x) \to \alpha_i I_i(x) \tag{2}$$

where the coefficients $\alpha_0, \alpha_1, \alpha_2$ are real values strictly greater than zero. This model was originally devised for narrow band sensors, but it has been proved to be a good approximation also for standard sensors (Finlayson et al., 1994).

When $\alpha_0 = \alpha_1 = \alpha_2 := \alpha$, the equation (2) describes a change of the image brightness, like that caused by shadows. In particular, when α is greater than 1, the image becomes brighter (i.e. the values of B increase), while when α is smaller than 1, the image becomes darker (i.e. the values of B decrease).

In agreement with this model, the algorithm REK rescales the channel intensities of any input image I by a parameter $\alpha > 1$. This operation, which is performed on the whole image I, enables improving the visibility of content and details of the dark regions, but at the same time it also increases the brightness of the bright area, with the risk of saturating the colors, removing edges and introducing unpleasant artifacts. To overcome this problem, REK combines the relighted image I^α with the input one through a summation whose addends are weighted by values depending on the brightness B of I and taking high values on the dark regions, while low values on the bright ones. Thanks to these operations, REK improves the visual quality of the dark regions, while preserves that of the bright regions.

Operatively, REK works as follows. First, REK maps I on a new image I^α, obtained by relighting I according to the von Kries model. Precisely, for each pixel x, the color channels of I^α are defined pixel by pixel as follows:

$$I_i^\alpha(x) = \alpha I_i(x) \tag{3}$$

with $\alpha > 1$ and i = 0, 1, 2.

Second, REK combines the input image I with I^α and

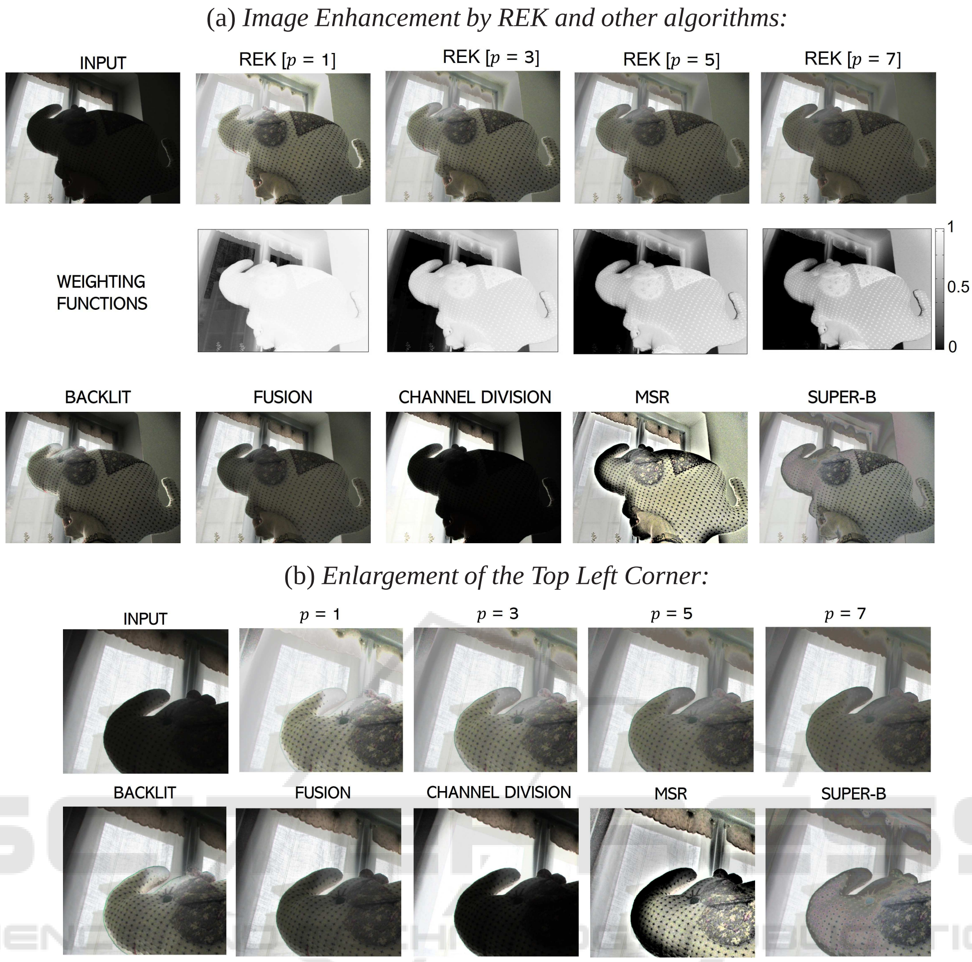

Figure 1: (a) On top, an image and its versions relighted by REK for $p = 1, 3, 5, 7$. In the middle: the weights corresponding to the different values of p. On bottom: image enhancement by other algorithms (see text for more explanation). (b) An enlargement of the top left corner of the input image and of its enhanced versions.

outputs a new, color image J, whose components J_i (i = 0, 1, 2) are computed pixel-by-pixel as follows:

$$J_i(x) = (1 - w(x))I_i(x) + w(x)I_i^{\alpha}(x), \tag{4}$$

where w is a weighting function, defined over the pixels of I, ranging over [0, 1], and taking high values on the dark regions, while low values on the bright ones.

There exist different equations for w. In the current implementation of REK, w is defined from B, precisely, for each pixel x:

$$w(x) = \left(1 - \frac{B(x) - m_B}{M_B - m_B}\right)^p \tag{5}$$

where m_b and M_B are respectively the minimum and the maximum values of B and p is an integer number greater or equal than 1. The value $p = 0$, that is not considered here, is a special case, in which w is identically equal to the constant function 1. Therefore, for $p = 0$, the input image does not contribute to the computation of J and the output image is completely defined by the von Kries transform.

Figure 1(a) shows in the first row an input image and four versions of it improved by REK with p = 1, 3, 5, 7. The second row of the figure displays the corresponding weighting functions: it is possible to observe that the gap between the values of w on the dark and bright regions increases with p. This means that the contribution of the bright regions from I^{α} decreases when p increases, so that the bright regions in the output image J are very similar to those in the input image, while the dark regions in the output image are brighter than their counterpart in the input image.

3 EVALUATION

The performance of REK has been evaluated on two datasets, called respectively PDB and SDB. PDB consists of 20 real-world color images, that have been selected from a personal collection of the author ('P' stands for personal) and whose size range from 1580 $\times$ 1882 to 4160 $\times$ 3120 pixels. SDB contains 60 real world color images with a lower resolution than those of PDB ('S' stands here for small): their size vary from 102 $\times$76 to 432 $\times$ 576 pixels. SDB includes pictures from Pixabay (https://pixabay.com), from some datasets used to test image enhancement algorithms, e.g. (Wang et al., 2016), (Li and Wu, 2018), (Ramirez Rivera et al., 2012), and some images from PDB at a low resolution. SDB was also employed to test the backlight/spotlight image enhancer described in (Lecca, 2021). In both the datasets, the images depict indoor and outdoor environments, acquired under natural or artificial backlight and spotlight (see e.g. Figures 1 and 2).

The performance of REK has been evaluated by analyzing three numerical features that are strongly related to the human perception of the image quality and are usually changed by enhancement. These features are described here using the notation introduced in Section 2:
The *entropy of the color distribution* (f_0), which is defined as the L^1 distance between the probability density function (pdf) of B and the uniform probability density function over [0, 255];
The *mean value of the image brightness* (f_1), i.e. the mean value of B;
The *standard deviation of the image brightness* (f_2), i.e. the departure of the image brightness from f_1.

The features f_0, f_1 and f_2 measure respectively the colorfulness, the brightness level and the contrast of the image I. These features usually change after enhancement, but their behaviour is expected to be different when they are computed on the bright regions, on the dark regions and on the whole image. Precisely, on the bright regions, where the visibility of details and content are generally already good, f_0, f_1 and f_2 are expected to remain stable or change slightly. In general, it may happen that the value of f_1 increases slightly, consequently the histogram of B on these regions becomes more peaked while the contrast diminishes because of saturation effects, i.e. f_0 increases and f_1 decreases. On the contrary, on the dark regions, f_1 and f_2 are both expected to increase, meaning that the areas become brighter and more contrasted, while f_0 is expected to decrease, since the enhancement tends to stretch the color distribution. Finally, on the whole image, f_1 is expected to increase, because the dark regions are brighter, while f_2 is expected to remain unchanged or to decrease slightly. In fact, brightening the dark regions decreases the contrast between the dark and the bright regions of the original backlight/spotlight image, that is usually very high. Consequently, the mean value of f_2 over the whole image generally decreases. Nevertheless, the exact behaviour of f_2 depends on the content of the dark regions: in fact, in case the dark regions contain very high color variations, the global value of f_2 may even increase. Moreover, it is to note that in the backlight and spotlight images, the pdf of B is bimodal, with the left and the right peaks corresponding respectively to the dark and bright regions. Brightening the dark areas stretches the left peak toward the right one and this diminishes the value of f_0 over the whole image.
To capture these different trends, the values of the measures listed above are here computed separately on the whole image and on their bright and dark areas and indicated respectively with f_is, f_i^bs and f_i^ds. To this purpose, the dark regions P_d and the bright regions P_b of the input image I are detected by a segmentation procedure that partitions B using a threshold τ. Specifically:

$$P_d = \{y \in D(I) : B(x) \leq \tau\} \quad (6)$$

$$P_b = \{y \in D(I) : B(x) > \tau\} \quad (7)$$

where $D(I)$ is the set of pixels of I and

$$\tau = \frac{M_B - m_B}{2}. \quad (8)$$

Finally, it is to note that, for a fair assessment of the performance of an enhancement algorithm, a single measure does not suffice. In fact, for example, a very high value of brightness may correspond to a saturated image, and thus to a loss of details and to a peaked distribution. Therefore, all the features described above, computed on the whole image or on its parts, must be considered simultaneously in the evaluation process.

The performance of REK has been evaluated also in comparison with the methods FUSION (Wang et al., 2016), BACKLIT (Li and Wu, 2018) CD (Ramirez Rivera et al., 2012), SuPeR-B (Lecca, 2021) and MSR (Petro et al., 2014), briefly described in Section 1. For the comparative analysis, the codes provided by the authors and/or available on the net on GiThub (FUSION and BACKLIT) and MatLab (MSR) repositories have been employed, within the parameters set as per default. For SuPeR-B, the number of pixels sampled over the images and the other three parameters, have been fixed respectively to 100 and zero (see (Lecca, 2021) for more details).

Regarding REK, the experiments have been repeated for different values of p, i.e. p = 1, 3, 5, 7. It is to note that, the parameter α must be chosen to prevent the intersection of the brightness distribution curves around the peaks corresponding to the dark and

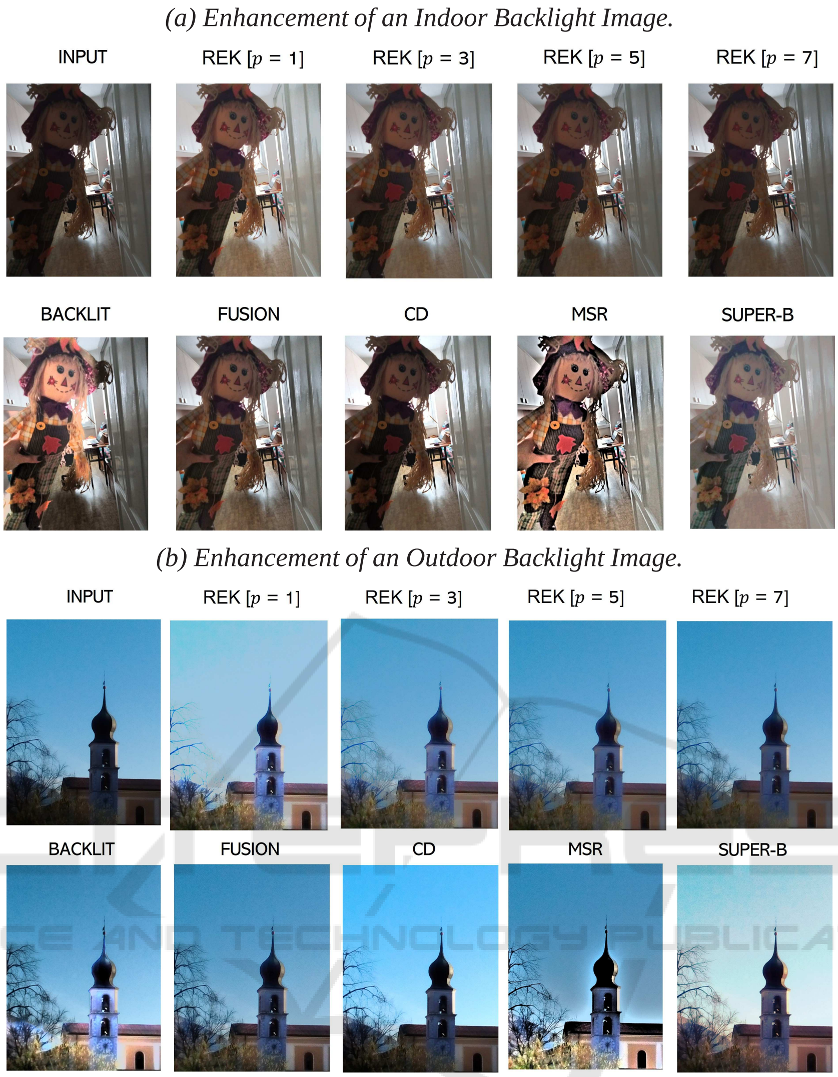

Figure 2: Examples of backlight/spotlight image restoring by REK with different values of p and by other enhancers.

to the bright areas: violating this prescription may cause the loss of the boundaries between the dark and bright areas, worsing the global quality of the image. To avoid this undesired effect, here α has been set as:

$$\alpha = \frac{\mu_B - \delta_B}{\mu_D}, \tag{9}$$

where μ_B and δ_B are respectively the mean value and the standard deviation of B over P_b, and μ_D is the mean value of B over P_d. Of course, it is supposed that $\mu_D > 0$, i.e. the dark region is not uniformly black.

4 RESULTS

Tables 1 and 2 report the mean values of the objective measures f_is, f_i^b and f_i^d computed on the datasets PDB and SDB. On both the datasets and for any value of p, REK effectively improves the quality of the dark images, but the best results are obtained for $p = 3$ and $p = 5$. In fact, for these values the bright regions are slightly modified, while the dark ones are remarkably improved, reporting a much higher brightness and contrast, while a lower entropy of the brightness distribution. Globally, the input image is brightened, while its contrast decreases because, as discussed in Section 3, after the enhancement, the difference between the dark and the bright regions diminishes. Consequently, the entropy of the brightness distribution is lower and the pdf is more uniform: usually, this means that the range of colors in the image has been widened and the image appears more pleasant. On the contrary, for $p = 1$, the bright regions are over-enhanced. their brightness increases very much,

Table 1: Evaluation of REK in comparison with other enhancers on the dataset PDB.

Algorithm	f_0 $[\times 10^{-3}]$	f_1	f_2	f_0^b $[\times 10^{-3}]$	f_1^b	f_2^b	f_0^d $[\times 10^{-3}]$	f_1^d	f_2^d
INPUT	4.16	71.00	65.89	4.93	197.76	31.45	5.12	33.86	25.88
BACKLIT	2.40	109.96	63.91	4.73	199.33	29.55	2.70	86.50	52.10
MSR	2.54	126.87	58.98	4.65	183.57	29.83	2.51	108.93	57.26
CD	4.07	89.46	79.97	6.13	235.28	17.29	4.34	45.00	40.87
FUSION	3.33	95.77	58.76	4.84	203.06	29.19	4.21	64.82	30.46
SuPeR-B	3.06	127.62	58.69	5.47	217.29	24.19	3.78	97.32	38.11
REK [p = 1]	3.54	134.21	63.81	6.11	214.63	18.14	3.48	110.89	57.16
REK [p = 3]	3.48	114.95	55.87	5.18	199.94	28.89	4.31	90.22	39.35
REK [p = 5]	3.72	105.23	55.12	4.98	198.02	31.04	4.77	77.79	30.79
REK [p = 7]	3.94	98.97	55.79	4.94	197.76	31.44	4.99	69.50	26.44

Table 2: Evaluation of REK in comparison with other enhancers on the dataset SDB.

Algorithm	f_0 $[\times 10^{-3}]$	f_1	f_2	f_0^b $[\times 10^{-3}]$	f_1^b	f_2^b	f_0^d $[\times 10^{-3}]$	f_1^d	f_2^d
INPUT	4.17	67.79	64.13	4.92	179.33	28.56	5.26	29.74	28.00
BACKLIT	2.78	100.65	65.67	4.68	189.30	29.14	3.47	73.26	51.58
MSR	2.21	118.12	61.97	4.69	185.23	27.82	2.35	97.24	58.55
CD	4.04	89.45	83.03	5.86	228.30	18.82	4.53	41.49	44.58
FUSION	3.23	89.54	60.81	4.84	189.51	26.62	4.22	56.82	34.50
SuPeR-B	3.17	119.31	64.77	5.51	213.03	21.25	3.95	84.12	41.38
REK [p = 1]	3.80	122.76	68.53	6.24	204.04	14.21	3.76	97.15	63.13
REK [p = 3]	3.51	103.75	57.55	5.23	182.86	25.44	4.35	78.60	44.68
REK [p = 5]	3.61	95.29	55.36	4.98	179.80	28.03	4.72	67.98	35.80
REK [p = 7]	3.76	90.21	55.18	4.92	179.34	28.54	4.90	61.10	31.13

their brightness histogram become more peaked, and their contrast decreases, meaning that some edges are lost. An example of these effects is shown in Figure 1, where the elephant's trunk becomes almost white and its final part tends to disappear (see Figure 1(b)), getting worse the quality of the entire image. It is to note that an excessive brightening may introduce artifacts also in the dark areas, as illustrated in Figure 2(b). Here, the image obtained for $p = 1$ presents some bluish halos on the bell tower, while the branches of the tree are poorly visible. For $p = 7$, the bright regions after enhancement are highly similar to the input one, while the dark regions have still a low contrast, very close to that of the input images. This means that the enhancement poorly improved the visibility of the details in the dark areas. As already observed in Section 2, these results are due to the different shape of the function w.

From the comparative analysis of REK with other methods, it results that CD often returns images where the dark regions are still quite dark, while the contrast of the bright regions is significantly reduced. MSR returns very good values of the f_is, f_i^bs and f_i^d, but a qualitative inspection of the images showed that the MSR images are poorly natural and look as cartoonized, with strong, thick edges between the dark and the bright regions. BACKLIT performs quite well, but sometimes generates undesired artifacts, like the halos visible on the bell tower of Figure 2(b) and the greenish, thin boundary around the elephant's trunk in Figure 1(b). SuPeR-B works generally well, but on average the edges in the bright regions are quite attenuated and, despite the visibility of the content and details is generally good, the global image appears often washed out. FUSION provides satisfactory results, but the improvement of the dark regions is less than that performed by REK. From the theoretical point of view, REK behaves similarly to FUSION, because both these methods merge images with different enhancement levels. Nevertheless, FUSION has an higher computational complexity since it computes three different enhancement versions of the input image and requires smoothing operations, while REK computes only one new image, i.e. that relighted by the von Kries model, and does not need for further processing.

5 CONCLUSIONS

The experiments described in Section 4 show that algorithm REK is a new, computational efficient backlight/spotlight image enhancer, outperforming other algorithms in the state-of-the-art. This result is obtained by up-scaling the channel intensities of the input image by the von Kries transform and blending the relighted image with the input one. In this operation the choice of the up-scaling factor α and of the weighting function w is crucial. In particular, the value of α must prevent over-enhancement effects as well as the removal of important edges, while w must grant simultaneously the improvement of the visibility of the dark regions and the fidelity of the bright regions to the original versions. The unsupervised estimate of α and the choice of an exponential function of the image brightness for w proposed here have been demonstrated to work well, especially when the exponent of w is equal to 3 and 5. In particular, for $p = 3$, after enhancement, the appearance of the bright regions is preserved, while on average, the values of the brightness and the contrast of the dark regions are increased by 165% and 56% with respect to their original values, while the color distribution entropy is decreased by 16.6%. Although these results are good, future research will investigate alternative choices, especially for the value of α. This latter currently relies on the analysis of the bimodal density function of the input brightness, but other possible choices could be considered also the weight w. Moreover, it is to note that the level of enhancement could be also made dependent on the application scenario, e.g. making the pictures more pleasant for entertainment, enabling visual inspection or computer vision tasks requiring high detail visibility, as for instance unsupervised image description and matching.

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