A Basic Tool for Improving Bad Illuminated Archaeological Pictures

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Abstract: Gathering visual documentation of archaeological sites and monuments helps monitor their status and preserve and transmit the memory of the cultural heritage. Good lighting is essential to provide pictures with clear visibility of details and content, but it is a challenging task. Indeed, illuminating a site may require complex infrastructures, while uncontrolled lights may damage the artifacts. In this framework, computer vision techniques may greatly help archeology by relighting and/or improving the images of archaeological objects that cannot be acquired under a good light. This work presents MEEK, a basic tool to improve low-light, back-light and spot-light images, increasing the visibility of their details and content, while mitigating undesired effects due to illumination. MEEK embeds three algorithms: the Retinex inspired image enhancer SuPeR, the backlight and spotlight image relighting method REK, and the popular contrast enhancer CLAHE. One or more of these algorithms can be applied to the input image, depending on the light conditions of the acquired environments as well as on the final task for which the image is used. Here, MEEK is tested on many archaeological color pictures with bad light showing good performance. The code of MEEK is freely available at https://github.com/MichelaLecca/MEEK.

1 INTRODUCTION

Archeology enables us to learn about the past and build the future based on the experience of our ancestors. Preserving and monitoring the condition of ancient artworks, like archaeological sites, paintings, mosaics, monuments, is the key to passing on a wide cross-section of human knowledge to future generations. In this context, computer vision techniques can be of great help in collecting visual documents of important past artifacts, classifying them according to their visual features, monitoring sites from satellites, as well as planning non-intrusive actions for their conservation and renovation (van der Maaten et al., 2006), (Brutto and Meli, 2012), (Traviglia et al., 2016), (Engel et al., 2019), (Resler et al., 2021), (Monna et al., 2021). For all these tasks, good light conditions are essential to obtain pictures where the content and the details of the objects of interest are clearly visible. Nevertheless, in general, such a requirement is hard to be satisfied and may need for complex, expensive infrastructures. This is the case with objects positioned in hard-to-reach places and paintings that can be damaged by uncontrolled lights. In this context, image enhancement techniques provide non-invasive solutions to recover better, global and local visibility of the content and details of the acquired scene.

This work presents a basic tool for enhancing pictures captured under low-light, backlight and spotlight. Low-light is weak illumination that produces dark pictures, while backlight and spotlight are highly non-uniform lights that generate images with both dark and bright regions. All these illuminations are common in archaeological environments. For instance, low-light is typical of excavations and crypts; backlight is usual in churches and castles, where windows/celling roses and small slits or crevices let in an intense but not diffused light; spotlight is present in places with works in progress or near breakable, delicate stuff, where an artificial source highlights specific objects while obscuring the rest of the scene. The presented tool, called MEEK from the key-expression iMage EnhancEment Kit, embeds three general purpose image enhancers that can be used individually or combined together to improve the quality of the input image. These enhancers are the Retinex inspired method SuPeR (Lecca and Messelodi, 2019), the backlight image enhancer REK (Lecca, 2022b), and the well known contrast enhancer CLAHE (Zuiderveld, 1994). These algorithms have been chosen among many others because of their low complexity and low number of parameters (one per

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algorithm), as well as their performance. In particular, both SuPeR and REK enhance the input image by a pixel-wise, non linear rescaling of the intensity values of the image channels. Precisely, SuPeR samples a set of high intensity pixels over each channel and uses them to process the colors of the other image pixels increasing the brightness and contrast of the input image, while mitigating possible chromatic dominants of the light. REK is a fusion-based enhancer specifically designed for backlight and spotlight images. It combines the input image with an over-enhanced version of it through a weighted sum so that the dark regions are improved while the bright ones are preserved. Differently from SuPeR, REK does not change the image chromaticity, i.e. the light color is neither removed nor attenuated. Finally, CLAHE stretches the distribution of the image brightness (or of the image channels, depending on the implementation) to increase the image contrast while limiting the amplification of possible noise. As already mentioned above, these algorithms can be used individually or applied sequentially upon the input image. For instance, a backlight image can be processed first by REK to improve the dark areas, then by SuPeR to smooth possible chromatic casts of the light, and finally by CLAHE to further enhance the contrast. Here, the algorithms of MEEK and some combinations of them have been tested on many real-world archaeological images and discussed on some relevant examples. The code of MEEK is released for free online (Lecca, 2022a).

2 MEEK

This Section describes the three algorithms included in MEEK and the MEEK interface and usage.

2.1 SuPeR

SuPeR (Lecca and Messelodi, 2019) is an image enhancer inspired by the Retinex theory (Land et al., 1971). As Retinex, SuPeR takes as input a color image J, processes pixel-wise its color channels independently, and returns a new image, in which brightness and contrast are increased, the color distribution is more uniform and possible dominants of the light are mitigated or even removed.

Specifically, SuPeR partitions J from a regular grid with n tiles $T_1, \ldots, T_n$, where $n > 1$ is an user input. For each tile, SuPeR computes the barycenter b_i of T_i, and for each channel I it computes the set $T(I)$ of the n pairs (b_i, I_i) where I_i the maximum value of I over T_i. Then, for any pixel x of I, SuPeR maps $I(x)$ on a new value $S(x)$ given by

$$S(x) = \frac{I(x)}{w(x)} \tag{1}$$

where $w(x)$ is a strictly positive value computed from $T(I)$. Zero division is of course prevented. Precisely, w is given by:

$$w(x) = \begin{cases} \left(\frac{\sum_{(b_i,I_i) \in B_I(x)} \frac{\delta(x,b_i)}{I_i}}{\sum_{(b_i,I_i) \in B_I(x)} \delta(x,b_i)} \right)^{-1} & \text{if } B_I(x) \neq \emptyset \\ I(x) & \text{otherwise} \end{cases} \tag{2}$$

where $B_I(x)$ contains the pairs of $T(I)$ whose intensity exceeds $I(x)$, i.e.:

$$B_I(x) \subseteq T(I) = \{(b_i, I_i) \in T : I_i > I(x)\} \tag{3}$$

and

$$\delta(x, b_i) = 1 - \frac{\| x - b_i \|^2}{D^2} + \varepsilon. \tag{4}$$

In this last equation, $\| \cdot \|$ indicates the L^2 norm, D is the length of the diagonal of the image support and ε is a small, strictly positive value introduced to prevent division by zero. S is then remapped to range over $\{0, \ldots, 255\}$. The three processed channels are then packed into a new RGB image.

It is to note that re-working $I(x)$ based on both color and spatial features is a distinctive trait of Retinex and is faithful to some aspects of the human vision system. Moreover, since $S(x)$ is a linear combination of the ratios $I(x)/I_i$s, it is robust to changes of illumination. In fact, according to the von Kries model, in a digital image, any change of color due to a change of light is well approximated by a linear diagonal transform (Finlayson et al., 1994), (Lecca, 2014). Consequently, local intensity ratios and their linear combinations are invariant against illuminant variations.

The name 'SuPeR' comes from the fact that this algorithm extracts the visual and spatial information relevant to image enhancement from blocks of pixels (i.e. the tiles), that are treated as super-pixels and each of them is represented by a position (i.e. the tile barycenter) and an intensity value (i.e. the maximum intensity over the tile).

2.2 REK

The algorithm REK (Lecca, 2022b) takes as input a color image J with strong backlight or spotlight and up-scales its color channels by a value α strictly greater than one, i.e. J is mapped onto image K by the following equation:

$$K(x) = \alpha J(x). \tag{5}$$

According to the von Kries model, this up-scaling operation brightens up the dark regions, increasing the visibility of their details and content, but at the same tim, it may over-enhance the bright regions. To avoid over-enhancement, REK fuses J and K into a new image R defined as:

$$R(x) = (1 - W(x))J(x) + W(x)K(x), \qquad (6)$$

where W is a weighting function, that ranges over [0, 1] and penalizes (awards, resp.) the intensities of the dark (bright, resp.) pixels of J, while awards (penalizes, resp.) those of K. Precisely,

$$W(x) = \left(1 - \frac{U(x) - m}{M - m}\right)^p \qquad (7)$$

where U is the image luminance, i.e. [1]:

$$U(x) = 0.299 I_r(x) + 0.587 I_g(x) + 0.114 I_b(x), \qquad (8)$$

I_r, I_g and I_b are the red, green and blue image channels, m and M are the minimum and maximum values of U and p is a strictly positive, user parameter, controlling the shape of W.

Experiments presented in (Lecca, 2022b) indicate $p =$ 3 and $p = 5$ as suitable values for a good enhancement. Regarding the parameter α, REK estimates its value from U as follows:

$$\alpha = \frac{\mu_{\mathcal{B}} - \sigma_{\mathcal{B}}}{\mu_{\mathcal{D}}}, \qquad (9)$$

where $\mathcal{B}$ and $\mathcal{D}$ contain respectively the pixels with U greater than threshold τ and those with U smaller or equal than τ, $\tau = \frac{M-m}{2}$, while μ and σ denote respectively the mean value and the standard deviation of the set in the subscript. Within this estimate, REK pushes the luminance of the dark regions towards that of the bright regions without over-enhancing $\mathcal{D}$. Anyway, it is to note that when the bright region is close to white, the standard variation $\delta_{\mathcal{B}}$ is close to zero and thus $\mu_{\mathcal{D}}$ is mapped to $\mu_{\mathcal{B}}$: in this case, there is the risk of saturating some pixels in the dark regions and manual intervention is needed to lower the value of α.

2.3 CLAHE

Increasing the visibility of image details is very important in archeology to visualize and describe local structures like inscriptions, mosaic tiles, signs of erosion possible present on surfaces. This task can be achieved by histogram equalization (HE), that reworks the distribution of the image luminance (or of the image colors, depending on the implementation) to obtain a new image with flatter distribution and higher contrast. For sake of simplicity, consider the luminance L. HE computes the histogram h of L, normalizes it so that h ranges over [0, 1], and applies to the image intensity values $k = 0, \ldots, Z-1$ the following transformation:

$$T(k) = \text{floor}\Big((Z-1)\sum_{j=0}^{k} h(j)\Big), \qquad (10)$$

where Z is the number of possible intensity values (usually 256) and function floor rounds down its argument to the nearest integer value. Better performance is reached by the so-called adaptive methods, which basically apply HE over multiple image patches in order to enhance local contrast. One drawback of these methods is the amplification of possible image noise, especially in near-uniform areas, that have a peaked histogram. The popular *C*ontrast *L*imited *A*daptive *H*istogram *E*qualization (Zuiderveld, 1994) (CLAHE) mitigates this effect, by clipping the histogram at a predefined threshold c (called the *clip limit*) before to compute T. The values exceeding the clip limit are re-distributed equally among the histogram bins, so that the integral of h over the intensity levels remains equal to 1, while h becomes flatter. Function T is then applied by considering as h the new, clipped histogram. The lower c, the slighter the distribution stretching is and the less evident the enhancement of the contrast is.

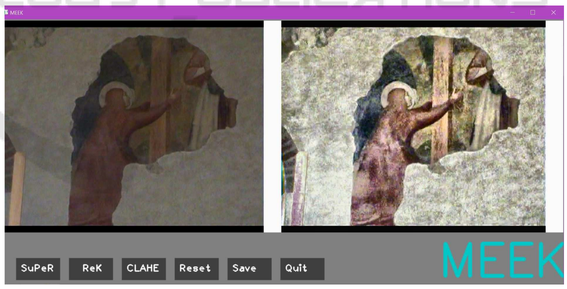

Figure 1: Interface of MEEK: on left, an image (from Ravenna-Set), and on right its enhancement by SuPeR followed by CLAHE.

2.4 MEEK Interface

MEEK (Lecca, 2022a) is implemented in C++ exploiting the image processing library OpenCV (https://opencv.org/). After compilation, MEEK can be used from a shell with the following syntax:

```
meek <input_image> <parameter.txt>
```

where `meek` is the executable file, `<input_image>` is the input image and `<parameter.txt>` is a text file containing the values of the parameters of the three

[1] In some implementations, like that described in (Lecca, 2022b), $U(x)$ is defined as the mean value of the channel intensities at x, instead of a weighted sum of them. This difference generally does not affect the final result.

algorithms, i.e. n for SuPeR, p and α for REK and c for CLAHE. Setting $\alpha = -1$ enables the automatic estimation of α.

Figure 1 shows an example of the MEEK interface. The first three buttons at the bottom must be pressed to run SuPeR, REK and CLAHE. The enhancement result will be displayed to the right of the input image. The button 'Reset' allows re-starting the enhancement on the input image. Combination of enhancement can be done by pressing sequentially the buttons of the corresponding algorithms. For example, to apply SuPeR and then CLAHE, the user presses first the SuPeR button, waits for the result and then presses the CLAHE button. The 'Save' button allows to save the result in the same directory of the MEEK executable file. Finally, the 'Quit' button stops the program and closes the window. In this implementation, CLAHE is applied on the luminance image channel, i.e. on the L component of the image represented in the Lab color space.

3 RESULTS

MEEK has been tested on 155 color indoor pictures, grouped in three dataset named Trento-SASS, Ravenna-Set and Backlit-Set.

Trento-SASS consists of 80 images, with size 1504×1004, portraying the rests of the ancient, roman city of Trento (Tridentum), which was brought to light during the restoration of the Social Theater of Trento between 1990 and 2000. These rests occupy a wide space of 1700 squared meters about and are located a few meters below the current level of the city. Due to their location, the images of such ruins are low-lighted and/or present moderate backlight and spotlight. The adjective 'moderate' indicates that the gap between the dark and the bright regions is neither too small nor too high, in particular for most images the luminance is low also on the bright regions (see Figures 2 and 3(right) for some examples).

Ravenna-Set contains 75 images, with size 720×576, taken by the author in Ravenna (Italia), specifically in the Mausoleum of Galla Placidia (first half of the 5th century AD) and in some churches with frescoes and mosaics, such as the Basilica of San Vitale (530 AD about), the Basilica of San Giovanni Evangelista (420 DC about) and the Basilica of San Francesco (13th century). Also these pictures are low-lighted and have moderate backlight/spotlight. In particular, the images captured in the Mausoleum of Galla Placidia are very dark, because no lights and no camera flashes were allowed (see Figure 3, left).

Backlit-Set contains 12 strong backlight images, partly downloaded from the free repositories pexels [2] and pixabay [3], and partly acquired by the author (see Figure 4). Nine pictures depict windows roses, while three others show monuments acquired against sky. These images are used to assess the performance of REK in comparison with SuPeR.

All the images from these datasets have been processed by SuPeR, REK, CLAHE, SuPeR followed by CLAHE and REK followed by CLAHE.

The performance of SuPeR, REK, CLAHE and of their combinations considered here is assessed by three numerical, objective measures, related to the human perception and usually modified by enhancing, i.e.:

1. The mean image brightness f_0, i.e. the mean value of the sum of the three color channels. Indicated by I_r, I_g and I_b the color channels of an image J, the brightness of J is defined pixel by pixel as $b(x) = \frac{I_r(x)+I_g(x)+I_b(x)}{3}$ and f_0 is the average of b over the number of pixels; f_0 is related to the global visibility of the image content;
2. The mean, multi-resolution image contrast f_1 (Rizzi et al., 2004), i.e. the mean value of the L^1 distance among any value $b(x)$ and its 8 neighborhoods, computed at different scales; f_1 captures local and global variations of b and is related to the detail visibility;
3. The index of the distribution flatness f_2, which is the L^1 distance between the probability density function of b and the uniform probability density function; f_2 is related to the image colorfulness.

In case of almost uniform low-light or moderate backlight/spotlight, the values of f_0 and f_1 should increase after enhancement, because the overall image is brightened up and its content and details become more visible. On the contrary, the value of f_2 should decrease: in fact, the enhancer restores the visibility of the content and details in dark areas and allows their color tones to be better distinguished. Consequently the brightness distribution flattens and f_2 becomes smaller. In case of backlight/spotlight, the f_is behave differently depending on the regions in which they are computed, i.e., the whole image, bright regions, and dark regions. On the bright regions, the f_is are expected to remain stable since these regions do not need enhancement, while on the dark regions, f_0 and f_1 are expected to increase (these regions becomes brighter and more contrasted after enhancing) and f_2 is expected to decrease (the brightness histogram, initially peaking to left, flattens with en-

[2]https://www.pexels.com/it-it/

[3]https://pixabay.com/

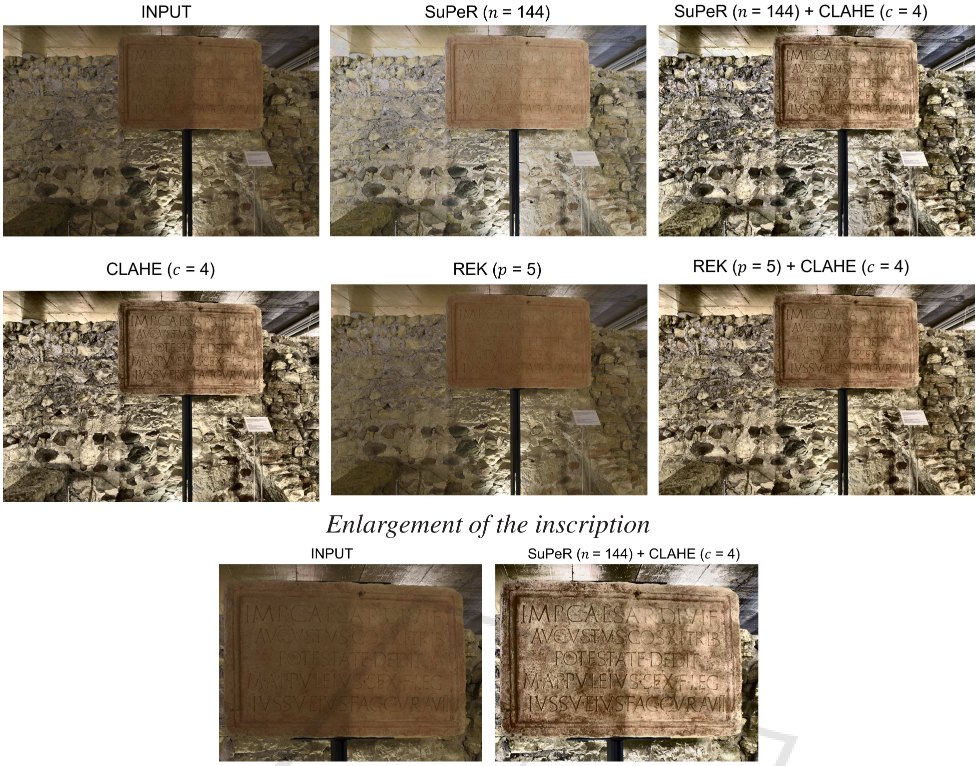

Figure 2: Enhancement of an image from Trento-SASS and enlargement of a part (input version and enhancement by SuPeR+CLAHE).

hancement). On the whole image, f_0 and f_2 should increase and decrease, respectively, due to the improvement of the dark areas. The behavior of f_1 is more complex and depends on the level of enhancement of dark areas. In fact, an enhancer increases the contrast of dark regions, but in this way it decreases the contrast between dark and bright regions. Depending on the proportion of dark and bright areas and their distribution in the image, the f_1 value calculated over the entire image may increase, remain stable, or even decrease, and thus it is irrelevant for enhancer evaluation. Therefore, on backlight/spotlight images, the enhancer performance are here assessed separately on dark and bright regions.

Finally, it is to note that the exact amount of the f_is depends on the image content. Moreover, for a fair evaluation, the measures f_0, f_1 and f_2 must be evaluated together. In fact, the analysis of a single measure usually does not provide an accurate assessment of the enhancement, since for example a high value of f_0 could correspond to a total saturation of the image: in this case, checking the values of f_1 and f_2 help to better describe and understand the enhancer performance.

Tables 1, 2, 3 show the values of f_0, f_1 and f_2 on the input and on the enhanced images from Trento-

Table 1: Performance of MEEK on Trento-SASS. The arrows indicate the expected trend of the measures. The parameters have been set empirically as follows: $n = 144$, $p = 5$, $c = 4$, while α has been automatically estimated by REK.

Algorithm	f_0 $\nearrow$	f_1 $\nearrow$	$f_2[\times 10^{-3}]$ $\searrow$
INPUT	64.01	12.79	3.94
CLAHE	94.07	26.94	2.19
SuPeR	110.66	16.31	2.92
SuPeR + CLAHE	118.27	31.20	1.45
REK	80.45	12.20	4.14
REK + CLAHE	111.41	29.14	1.76

Table 2: Performance of MEEK on Ravenna-Set. The arrows indicate the expected trend of the measures. Here, p and c have been set like in Trento-SASS, while n has been fixed to 100 and α has been computed by REK for all the images apart from four images, for which α has been set to 2.5 because the bright regions were almost white.

Algorithm	f_0 $\nearrow$	f_1 $\nearrow$	$f_2[\times 10^{-3}]$ $\searrow$
INPUT	74.37	14.06	4.14
CLAHE	96.76	27.44	2.30
SuPeR	126.92	17.77	3.31
SuPeR + CLAHE	122.25	31.79	1.63
REK	89.26	13.28	4.33
REK + CLAHE	105.21	27.08	2.36

Table 3: Performance of MEEK on Backlit-Set broken down by bright and dark regions. The symbols under the measures indicate the expected trend of the measures. The algorithms' parameters have been set like for Trento-SASS.

(a) *Assessment on Bright Regions*

Algorithm	f_0^b $\simeq$	f_1^b $\simeq$	$f_2^b[\times 10^{-3}]$ $\simeq$
INPUT	181.09	44.02	4.45
CLAHE	199.99	40.67	4.75
SuPeR	202.42	41.68	4.96
SuPeR + CLAHE	213.65	38.04	5.09
REK	181.76	36.30	4.52
REK + CLAHE	203.86	35.81	4.94
REK + SuPeR	203.96	32.67	5.09
REK + SuPeR + CLAHE	214.74	35.95	5.10

(b) *Assessment on Dark Regions*

Algorithm	f_0^d $\nearrow$	f_1^d $\nearrow$	$f_2^d[\times 10^{-3}]$ $\searrow$
INPUT	32.20	13.16	5.10
CLAHE	66.01	23.57	3.20
SuPeR	50.14	16.84	4.20
SuPeR + CLAHE	87.29	28.09	2.38
REK	61.84	15.35	4.53
REK + CLAHE	96.32	29.90	2.13
REK + SuPeR	87.53	19.22	3.61
REK + SuPeR + CLAHE	105.11	32.02	1.86

SASS, Ravenna-Set and Backlit-Set (in this last case, the measures are broken down by dark and bright regions). All these values are averaged over the number of images per dataset.

From Tables 1 and 2 it comes that for CLAHE, for SuPeR and for the combinations SuPeR + CLAHE and REK + CLAHE, the trend of the measures is as expected: f_0 and f_1 increase, while f_2 decreases, meaning that input images are brightened, their contrast is increased, while the luminance histogram is flattened. On both the datasets Trento-SASS and Ravenna-Set, REK returns the worst results, because most of these images have low-light or moderate backlight/spotlight and REK is specifically designed for strong backlight and spotlight. Therefore, on Trento-SASS and Ravenna-Set, REK increases f_0 less than the other methods do, and slightly decreases (increases, resp.) f_1 (f_2, resp.). Much better results are obtained by REK on Backlit-Set, whose images present strong backlight. On this dataset, REK has been also combined with SuPeR in order to mitigate or even remove possible color casts. Tables 3(a) and 3(b) report the objective measures on the sets $\mathcal{B}$ and $\mathcal{D}$ of the bright and dark regions. For sake of clarity, the measures computed on $\mathcal{B}$ and $\mathcal{D}$ have been indicated respectively by f_i^bs and f_i^ds ($i = 0, 1, 2$). REK improves all the values f_i^ds (i.e. it increases f_0^d and f_1^d, while decreases f_2^d), while maintains the triplet (f_0^b, f_1^b, f_2^b) closer to the original one than the other algorithms in terms of L^1 distance. Indeed, the other algorithms tend to over-enhance the bright areas: they generally increase very much their luminance while worse the flatness distribution index. Combined with CLAHE, REK and REK+SuPeR output good results, but the bright regions are less preserved than when only REK is used.

Figures 2, 3 and 4 illustrate the behaviour of the different algorithms on some archeological images from the three datasets, enabling the user a quick visualization of the enhancement results.

Figure 2 shows an image of the ancient city Tridentum. The image has a low, yellowish light and the characters of the inscription depicted in the middle are poorly readable in part because of the light and in part because of the time, that smoothed the stone surface. REK poorly changes the image quality, while SuPeR returns a brighter image. CLAHE reinforces the edges and the characters, but these latter are still not well readable. The combination of SuPeR and CLAHE returns the best result, where the light color is lowered and the inscription becomes clearer, as shown in the enlargement.

Figure 3 shows two images, one captured in the Mausoleum of Galla Placidia and the other in the ancient city of Trento. Both the images have been acquired under low-light with a moderate backlight. All the enhancers brighten up the scene very much, but the best results are obtained by SuPeR and REK combined with CLAHE, which reinforces the improvement of the contrast. Again, differently from CLAHE and REK, SuPeR enables the removal of the yellowish chromatic dominant of the light.

Figure 4 shows the enhancement obtained by CLAHE, SuPeR and REK on a strong backlight image from Backlit-Set. In this case, CLAHE performs poorly: it remarkably increases the contrast, improving the detail visibility, but the overall content is not well visible. REK provides here the best result and also remarkably outperforms SuPeR. In fact, on this image, SuPeR divides the intensities of the dark pixels by the much greater maximum intensities of the bright tiles. Despite penalized by the spatial distance weights, these bright intensities heavily contribute to the final value of S on the dark regions, that remain still dark. Using a higher value of n may provide better results, as well as considering alternative weights (see for instance (Lecca., 2021)), but this tuning is usually hard, especially for non-expert users. In this context, REK offers a simpler and more computational efficient enhancement method with much better results.

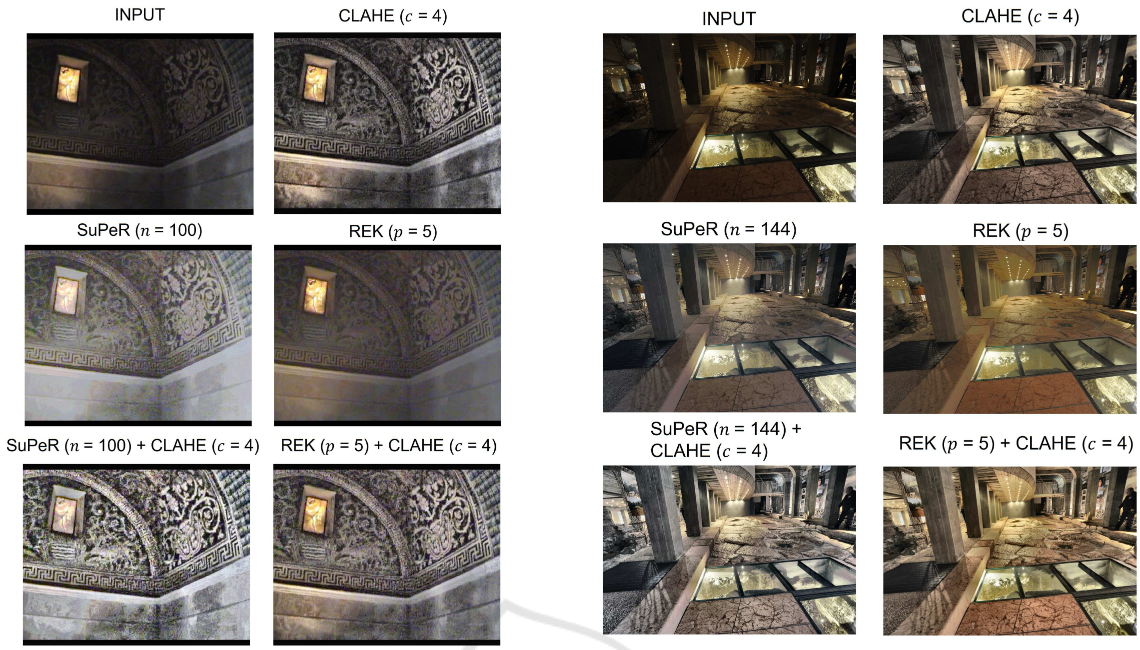

Figure 3: Examples of enhancement by MEEK on images from Ravenna-Set (on left) and from Trento-SASS (on right).

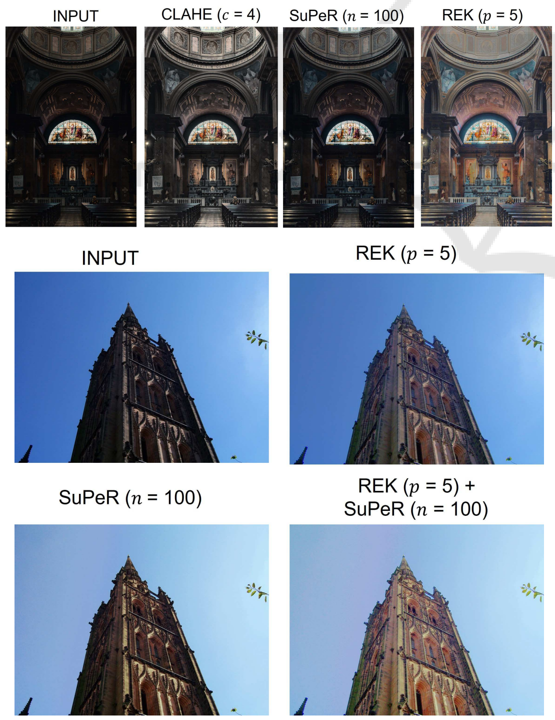

Figure 4: Examples from Backlit-Set. On top, image enhancement by CLAHE, SuPeR and REK; on bottom, image enhancement by REK, SuPeR and REK+SuPeR.

4 CONCLUSIONS

This work presented MEEK, i.e. a new, basic tool for the enhancement of images captured under uniform and non-uniform low-light, strong backlight/spotlight and colored light. Such difficult light conditions are typical of archeological environments and represent a bottleneck for collecting high quality visual documents of these places. The experiments carried out on archeological images of excavations, churches, rose windows, mosaics, frescoes show that the three enhancers (SuPeR, REK and CLAHE) included in MEEK and their combinations effectively improve the quality of such images. In particular, SuPeR is suitable for increasing the content and details visibility of images with low-light and moderate backlight/spotlight. In addition, it attenuates or even eliminates possible chromatic dominants of the light. REK works well on images with strong backlight/spotlight, improving the visibility of details and content of the dark areas without over-enhancing the bright ones. Combining REK and SuPeR improves dark areas while diminishes possible light color casts. CLAHE increases the image contrast by modifying its color distribution. In this way, it improves the visibility of the image details. Coupling CLAHE with the other enhancers generally further increase their performance.

MEEK is only a first step in building an effective, easy-to-use, and more comprehensive tool for archaeological image enhancement. In fact, MEEK currently offers a generic image enhancement tool, but it could be complemented by alternative and/or additional algorithms adapted to archaeological image processing. In particular, MEEK could be expanded to include denoising techniques, which are often desired to reduce noise due to low illumination. In this context, a collaboration with archaeologists would be of considerable help both in testing the current version of meek as well as in indicating possible modifications and/or guiding the development of new ad-hoc techniques for the enhancement of visual documents. MEEK could also be equipped with deep learning image enhancers, e.g., (Liu et al., 2021), (Lv et al., 2021), possibly trained on archaeological images. Future research will therefore address these topics.

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