Adaptive Contrast Enhancement for Underexposed Images

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ABSTRACT

In the present article we focus on enhancing the contrast of images with low illumination that present large underexposed regions. For these particular images, when applying the standard contrast enhancement techniques, we also introduce noise over-enhancement within the darker regions. Even if both the contrast enhancement and denoising problems have been widely addressed within the literature, these two processing steps are, in general, independently considered in the processing pipeline. The goal of this work is to integrate contrast enhancement and denoise algorithms to proper enhance the above described type of images. The method has been applied to a proper database of underexposed images. Our results have been qualitatively compared before and after applying the proposed algorithm.

Keywords: contrast enhancement, denoise, underexposed images

1. INTRODUCTION

Global and local contrast correction algorithms have become very popular to improve the quality of the captured images (like those obtained with mobile devices among others) when underexposed and overexposed regions are simultaneously present within the image. In the literature, many algorithms have been proposed, from histogram equalization-type techniques[1,2] to other types of methods like the Retinex model[3] or local contrast corrections methods, where non linear masking is used in order to perform the local processing.[4,5]

In the present article we focus on enhancing the contrast of images with low illumination that present important or large underexposed regions. In this particular case, when applying the standard contrast enhancement techniques, we will also introduce noise over-enhancement within the darker regions. Noise not only changes depending on exposure setting and camera model, but it can also vary within an individual image. For digital cameras, darker regions will contain more noise than the brighter ones. Also the denoising problem has been widely addressed within the literature.[6–9] Noise is often assumed to be Additive White Gaussian Noise (AWGN). A widely used estimation method is based on Mean Absolute Deviation (MAD)[10] and different approaches have been proposed for noise estimation.[11–14] In some image denoising software, the user is required to specify a number of smooth image regions to estimate the noise level.

In general, these two processing steps (contrast enhancement and denoising) are independently considered in the processing pipeline. The goal of this work is to integrate contrast enhancement and denoise algorithms to proper enhance the above described type of images (for example night images or indoor images acquired with a short exposure time and/or high ISO setting). Therefore, not only the visibility of details is desired but also to control the noise level in the output image that should not be greater than the noise level of the input. Or even better, lower the noise with respect to the original shot.

In this work, in order to selectively enhance the different regions we consider the saliency map[15] of the image. The idea of performing different enhancing strategies with respect to the salience of the regions of an image where previously used by many authors, see for example Gasparini et al.[16]

The algorithm proposed in this article, through the use of saliency maps, aims to extract the meaningful information or Region Of Interest (ROI) of the scene that will be used to process the image selectively. After a

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first module of local contrast enhancement, the saliency map is computed. At this point, the local increase of noise is estimated. In a subsequent module, the denoise and final contrast correction are tuned with respect to the strength of the contrast and consequent noise increase and the local salience as well.

The paper is organized as follows. In section 2 our algorithm is presented, and the single modules are briefly described. In section 3 we present the experimental results. Finally, section 4 summarizes the conclusions.

2. METHOD OVERVIEW

Figure 1 shows the flow diagram of the proposed algorithm. The original image $I(x, y)$ is first contrast enhanced by an automatic local and global image-based correction. As we are working on images that present significantly underexposed regions, the noise in the darker zones may be significantly enhanced by this step. To overcome this undesirable loss in the image quality, our algorithm proceeds as follows: starting from this contrast enhanced image $I_c(x, y)$, a saliency map is computed. At the same time, the noise for each channel of the YCbCr color space is also estimated. In the salience adaptive denoising module, the Y channel of the local contrasted image $I_c(x, y)$ is processed applying a modified version of the bilateral filter.[9] The strength of the smoothing is a function of the estimated level of noise and is further weighted by the saliency map. Regions less salient are more blurred than regions that have been evaluated more significant by the saliency map. The chromatic channels Cb and Cr are processed with a Wiener filter using the estimated sigma of the chromatic noise.

The single modules of our method are described in the following subsections.

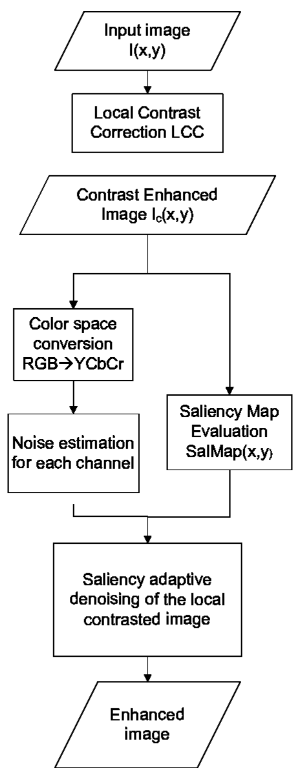

Figure 1. Flowchart of our algorithm.

2.1 Local Contrast Correction algorithm

The Local Contrast Correction (LCC) algorithm here adopted is based on the local and image dependent exponential correction presented by Schettini et al.[5] A brief description of the LCC method follows. The 'Gamma correction' is the simplest exponential correction common in the image processing field, and consists in processing the input image through a constant power function. This correction gives good results for totally underexposed or overexposed images. However, when both underexposed and overexposed regions are simultaneously present in an image, this correction is not satisfactory. Inspired by a previous work of Moroney,[4] the exponent of the gamma correction used by the LCC method is not a constant but depends on the point to be corrected (as in the case of the basic gamma correction), its neighbouring pixels and on the global characteristic of the image. The proposed algorithm applied to the channel intensity is:

$$I_c(x,y) = I(x,y)^{\alpha^{\left(\frac{128-mask(x,y)}{128}\right)}} \tag{1}$$

where $mask(x,y)$ is an inverted low-pass version of the intensity of the input image, filtered with a bilateral filter[9] and α is a parameter depending on the image properties: if the mean channel intensity is less or greater than 128, α is evaluated by equations 2 or 3 respectively:[5]

$$\alpha = \frac{log(\bar{I}/255)}{log(0.5)} \tag{2}$$

$$\alpha = \frac{log(0.5)}{log(\bar{I}/255)} \tag{3}$$

For low contrast images, where a stronger correction is needed, α should be high, while for better contrasted images, α should diminish towards 1, which corresponds to no correction. In the present implementation, working with color images, we apply the rule of equation 1 to each of the components in the RGB space. From a deeper analysis of the intensity histogram before and after the proposed local correction, it comes that, despite a better occupation of the grey levels, the overall contrast enhancement is not satisfying. In fact, the new histogram is more spread than the original but it is moved and concentrated around the middle values of the range. The effect that makes the processed image greyish is intrinsic in the mathematic formulation of equation 1 adopted for the local correction. To overcome this problem a further step of contrast enhancement, consisting of a stretching and clipping procedure, is added as detailed in.[5] However, this strategy is not sufficient to achieve good results in case of significantly underexposed images such as those considered in this work. As it can be seen from Figure 2, the LCC method works well for the first example image while for the second one, noise over-enhancement has been introduced within the darker regions.

2.2 Saliency map calculation

Saliency is a concept which states that there are regions in a scene that are more relevant than their neighbors and hence draw attention. Based on a biologically plausible architecture, Itti and Koch[15] implemented a saliency map model which makes use of color, intensity and orientation cues to predict salient regions in both simplified visual inputs and complex natural scenes. To reduce the computational complexity, in the present work we will use the simpler contrast-based saliency map proposed by Ma and Zhang.[17] The basic algorithm divides the image into small rectangular tiles. At each tile, a contrast score is computed from the differences of average colors between the given tile and its neighbor's tiles. The contrast score expresses the saliency of the pixels in the tile. The contrast scores of all the tiles define the saliency map of the image. The size of the tiles, and the size of the neighborhoods determine the dimensions of the salient areas that can be detected. The basic, single scale algorithm has been extended by Ciocca and Schettini[18] to compute three different levels of saliency maps. Using neighborhoods of increasing size, each aimed at a particular level of detail (small, medium and large) a multi-level saliency map was formulated. In the present work we choose to use only the high-details saliency map. In this way for each pixel (x,y) of the contrasted image $I_c(x,y)$ the saliency map called $SalMap(x,y)$, is obtained. As an example, in Figure 3 an image of our database and the corresponding saliency map are shown.

2.3 Noise estimation

For underexposed images, noise is not simply additive, but it is also strongly dependent on the image intensity level. Moreover, noise changes depending on the exposure setting and camera model and it can also vary within an individual image. Therefore, for the images we address in the present article, we ignore what type of noise

Figure 2. Original image (left column), the result after applying LCC method (right column).

is present in the image (addditive and/or multiplicative, chromatic and/or achromatic). For this reason, we are not interested here in estimating the noise level as a function of the image intensity. We are mainly interested in estimating noise within the darker regions. In these regions the original Signal to Noise Ratio (SNR) is significantly low and any contrast correction will increase the noise level, further reducing the initial SNR. We select as dark regions those corresponding to the first peak of the intensity histogram of the original image. The noise level is estimated within these regions in the contrast corrected image, as we are interested in the noise increase due to the enhancement (see the flowchart of our method shown in Figure 1). Moreover, as the noise in digital images is both chromatic and achromatic, we move to the YCbCr color space and we estimate noise for each channel, evaluating the corresponding standard deviations within the selected regions.

Figure 3. Example of the saliency map adopted in our method, obtained using only the high details

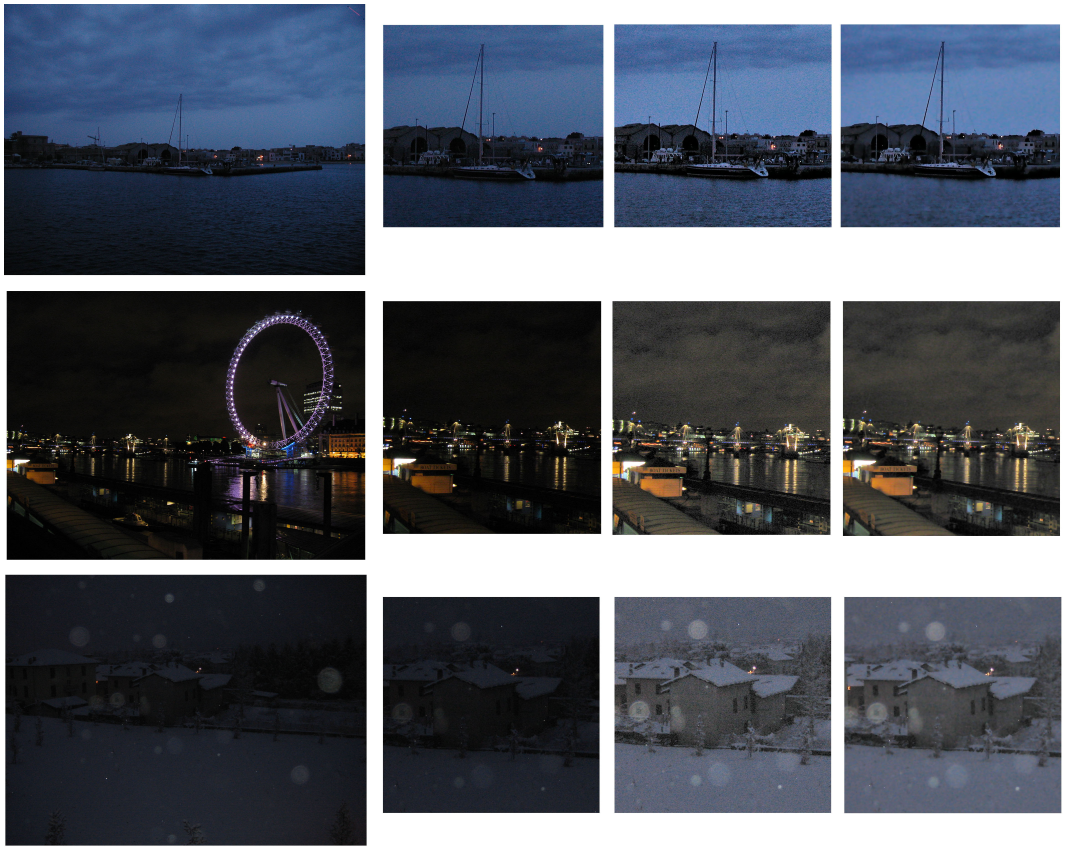

Figure 4. Original images (first column). A portion of the original image (secodn column). Corresponding portions of the images after the LCC method (third column). Our whole algorithm (last column).

2.4 Salience-adaptive denoising module

In our denoising module we apply different strategies to intensity and color channels.

For the intensity channel we adopt a modified version of the bilateral filter introduced by Tomasi and Maduchi.[9] The bilateral filter smoothes images while preserving edges, by means of a nonlinear combination of nearby image values. The idea is to do in the intensity range of an image what traditional filters do in its spatial domain. Two pixels can be close to one another, that is, occupy nearby spatial location, or they can be similar to one another, that is, have nearby values. The appropriate solution is to combine domain and range Gaussian filtering (depending respectively on a spatial standard deviation σ_s and on a range standard deviation σ_r). In this way, both geometric and photometric locality are simultaneously enforced. In our algorithm, the standard deviation σ_r of the Gaussian function in the range domain is related to the estimated intensity noise σ_{noise}. In particular, following the proposal of Liu et al[19] we set:

$$\sigma_r = 1.95\sigma_{noise} \tag{4}$$

Moreover, the strength of the filtering is weighted by the saliency map $SalMap(x, y)$ defined above, so that regions more visually salient are filtered less than region less significant. This effect is obtained making σ_r spatially varying, defining a new $\hat{\sigma}_r(x, y)$ as follows:

$$\hat{\sigma}_r(x, y) = \sigma_r(1 - SalMap(x, y)) \tag{5}$$

On the other hand, for each of the color channels Cb and Cr, we apply a Wiener filter, which is a filter adaptive with respect to the level of noise and specifically designed for additive noise. In our algorithm the reference value of noise for each channel is estimated as described above.

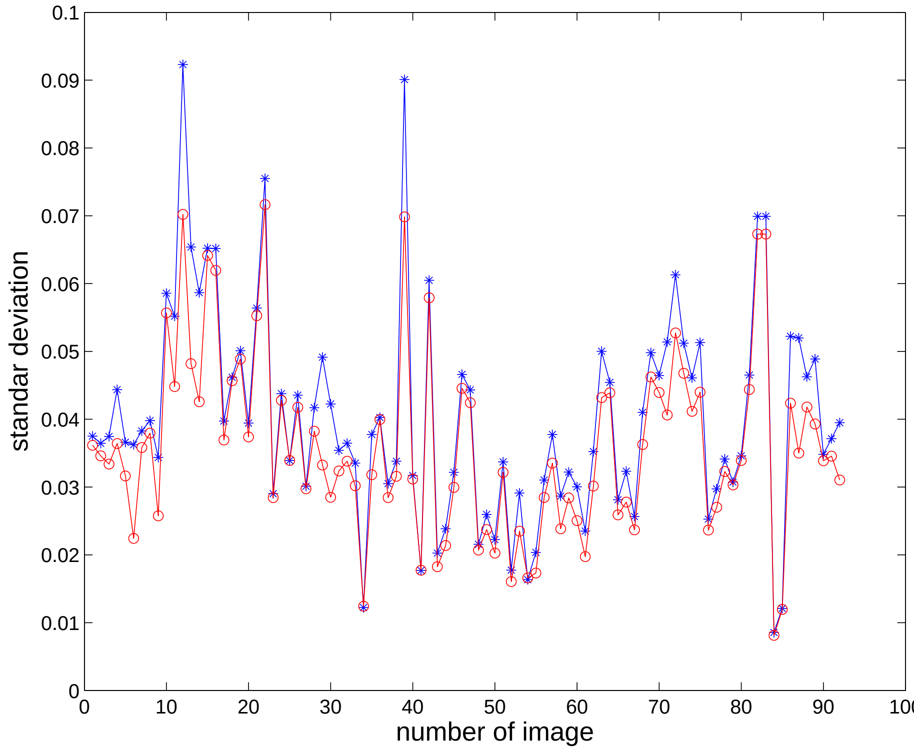

Figure 5. Local standard deviation for the 92 images of our database.

3. RESULTS AND DISCUSSION

We have applied our algorithm to 92 underexposed images, acquired with different devices, from high professional cameras to low quality hand phones.

In Figure 4 the results of the proposed method are shown for three example images. In the first column, underexposed original images are shown while a portion of each of them is depicted in the second column. In the third column the corresponding portions after the LCC method are shown. Finally in the last column the same regions after our whole algorithm are reported. Note that the noisy regions corresponding to the darker portions of the orginal images are smoothed more than regions more salient, where the high frequency details were preserved.

In order to compare the results, it is not easy to define reliable no reference quality metrics with normalized range of values. Moreover, it is even more difficult in the present case where the reduction of noise and the sharpness of the image should be simoultaneously taken into account. Therefore, we only report in Figure 5 the comparison of the mean local standard deviations (corresponding to the "dark regions") of the LCC images (blue-stars) and those obtained after our whole algorithm (red circles). As above mentioned, we have defined as "dark regions" those corresponding to the first peak of the intensity histogram of the original image. We observe from the figure that the higher values of the local standard deviation were reduced, while lower values were kept more or less equal (corresponding to images where the noise was already relatively low). This fact confirms the adaptive property of the method. A better analysis of the results requires also a subjective psychovisual test to be done in the future.

Figure 6. Original image (first row). Image processed with Retinex model and denoised Retinex (left column). Image after LCC and whole method here proposed (right column).

Up to our knowledge, methods that perform simultaneously contrast enhancement and denoising are not described in the literature. Therefore, in this article, we have limited the visual comparison of our results with the Frankle and McCann version of Retinex.[3] To make a fair comparison, after the Retinex contrast correction we have applied the bilateral filter (as denoising module); using the default values for the parameters of the bilateral filter ($\sigma_s = 3$, and $\sigma_r = 0.1$). In Figure 6 the results obtained applying our method and the output of the Retinex denoised by the bilateral filter are shown (hereafter called "denoised Retinex"). The first row shows the original image. In the left column, the Retinex and denoised Retinex results are shown. In the right column, LCC and our final proposal results are depicted. Our method seems to reduce the noise of the dark regions while maintaining a good level of the high frequency details.

4. CONCLUSIONS

In this work we have presented an adaptive enhancement procedure especially suited for underexposed images, where the noise level of the darker regions usually increases significantly after common contrast processing. To overcome this undesirable loss in the image quality, our algorithm adds a proper denoising module after a local and image dependent contrast correction. This denoising module is 'salience-adaptive' as it is weighted by the saliency map of the image. Moreover, its strength is piloted by the noise level of the image. Experimental results and a visual comparison with the well known Retinex method, reveal a significant noise suppression, without loss of details in the salient regions.

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