RESTORATION OF FADED IMAGES WITHOUT NOISE AMPLIFICATION

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ABSTRACT

This paper[1] focuses on an automatic model for contrast enhancement of digitized archive photographic prints. It exploits the relation between the change of contrast along scales and the Lipschitz regularity of the image for producing an adaptive enhancement. This strategy allows to drastically reduce typical effects as halo and noise amplification, resulting completely automatic thanks to the use of the visibility laws.

1. INTRODUCTION

Contrast enhancement is a well known and stimulating problem in image processing. It aims at giving images whose contrast is not optimal the original vividness. Among several approaches proposed in literature the most famous are the pioneering Retinex, based on Land's studies [1], and histogram equalization [2]. They received great attention and various improvements have been proposed. It is interesting to note that the evolutions of both approaches consider more than one scale (i.e various resolutions) and a context for estimating the enhancement [3, 4, 5, 6]. In fact, there is a general agreement about the fact that these two factors greatly improve the performance of any contrast enhancement framework [7]. However, all the aforementioned approaches have the drawback of producing side effects like the halo effect and over-amplification of fine details [8]. These problems stem from both the multi-resolution, based on convolution with smoothing kernels, and context based computations, based on a global measure in a suitable neighborhood, that are responsible of unavoidable artifacts as oversmoothing (with a loss of details) or excessive enhancement (with an annoying amplification of noise and/or halo effects). Even though some sophisticated approaches have been proposed for their reduction [9, 10], they remain the first aspect to consider in designing any contrast enhancement framework. In this paper we present a multiscale approach that exploits the local context for computing the contrast and then to produce an adaptive enhancement. It is based on the link between the change of contrast along scales and the local Lipschitz regularity of the image [11]. It is well known that the latter can be used for computing the noisy nature of pixels, avoiding convolutions with kernels that would introduce the aforementioned artifacts. On the other hand, the use of the contrast at different resolutions allows us to exploit the visibility laws in order to automatically regulate the importance and then the enhancement of each pixel of the image under study. Hence, according to pixels contributions within the image, this process changes their contrast. Then, a successive phase for achieving an optimal (global) gamma correction that exploits the results in [12] is performed. The proposed framework has been tested on various digitized historical photographic prints subjected to fading. The latter is characterized by a (global or local) loss of color vividness caused by chemical and physical agents on prints support [12]. A typical example of faded image is shown in Fig. 1. Experimental results show that the proposed approach achieves good results in terms of subjective quality and a good efficiency even in critical cases.

Figure 1: A typical example of faded photografic print: Horse rider.

2. THE PROPOSED MODEL

The proposed model is mainly based on three phases. The first one is a preprocessing. It aims at finding out those pixels that belong to regions affected by different kinds of damage. This operation allows a more correct estimation of the parameters in the successive two phases. The second phase exploits the link between the local Lipschitz regularity and the change of the contrast of the image. This way, an adaptive contrast enhancement can be performed on the faded image.

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Figure 2: Matrix of the contrasts of the image in Fig. 1.

After the first two phases, all the degradation in the image but fading, results attenuated. The third phase is oriented to defading the image through a contrast enhancement based on the classical characteristic curve z^α, with $\alpha > 1$. In order to automatically estimate the optimal value of α, we exploit the results contained in [12] based on the following observation: pleasant (from a visual point of view) images show a sort of orthogonality between first and second moment of the distribution of the luminance values. In the following the aforementioned phases are presented in detail.

2.1 Deblotching

The objective of the first phase, roughly named deblotching, consists of detecting regions whose color is much more visible than the information of the original (faded) image. These regions are usually caused by different kinds of degradation and appear as dark or bright blotches, as shown in Fig. 1. There are two main reasons for performing this operation. First, these blotches would increase their appearance (with respect to the remaining information) after any contrast enhancement operation. As a result, the defaded image would be masked by them, producing an annoying effect on the global visibility quality of the final result. The second reason is that these blotches have statistical properties that are completely different from the rest of the image. Hence, their elimination improves the estimate of the parameters involved in the two successive phases.

Detection of blotches is usually difficult because of their variability in shape and intensity. However, it seems a bit more easy in case of faded images because blotches appear somewhat evident in the faded context of the degraded image. Then, it is better to use the local contrast rather than the intensity of the image, since their appearance is overstressed, as shown in Fig. 2. In particular, the contrast is defined as

$$C(x,y,s) = \frac{I(x,y) - M(x,y,s)}{M(x,y,s)} \qquad (1)$$

where $I(x,y)$ is our faded image, $M(x,y,s)$ is the mean of I in a region $\Omega_{x,y}$ centered in x,y and s is the scale level (or resolution) at which we compute the contrast. Using this definition, directly tied to the Weber law, it is possible to note how blotches become a sort of outliers in the image. Hence, blotches can be easily detected by hard thresholding $C(x,y,s)$. The threshold th can be tuned either manually or by setting $th = 3\sigma$, where σ is the standard deviation of $C(x,y,s)$. The latter solution is robust under the hypothesis that blotches are evident, as in Fig. 1. The more the hypothesis is relaxed, the more the number of false alarms (good pixels recognized as blotches) increases. It is worth emphasising that this detection is quite rough, but it is just a preprocessing for making the successive computations more correct.

2.2 Lipschitz based Contrast Enhancement

Fading very often appears with noise that is usually caused by chemical degradation of the photographic emulsion. The aim of this phase is then to produce an image where the contrast of each pixel is changed according to its contribution: noisy, edge or flat region. The analysis carried out in this section is local, and we are not interested in the optimal value of γ for a z^γ correction. This will be the topic of the third phase. On the contrary, we are interested here in analyzing the link between the pointwise Lipschitz regularity and the contrast variation of the image. It well known that the Lipschitz coefficient gives information about the noisy nature as well as the regularity of each point [11].

In particular, bearing in mind the contrast definition in (1), we can compute the contrast variation along scales (i.e. changing the resolution) for the generic pixel located at (x_0, y_0):

$$\dot{C}(s) = -\frac{I\dot{M}(s)}{M^2(s)} = -(1+C(s))\frac{\dot{M}(s)}{M(s)} \qquad (2)$$

If we locally approximate the image $I(x_0,y_0,s)$ with a polynomial $P_\gamma(s)$ of degree γ in a neighborhood of (x_0,y_0), then the local background, i.e. the mean of I, is:

$$M(s) = \frac{1}{H^2 s^2}\int\int_{\Omega(s)} P_\gamma(x,y)dxdy \propto \frac{\overline{P}_\gamma(s)}{H^2 s^2}$$

where $\Omega(s) = [x_0 - (H/2)s, x_0 + (H/2)s] \times [y_0 - (H/2)s, y_0 + (H/2)s]$ and $\propto$ indicates the functional dependence. Hence[2], $\dot{M}(s) = \frac{\gamma\overline{P}_{\gamma-1}s^2 - 2s\overline{P}_\gamma}{H^2 s^4} = \frac{(\gamma-2)O(s^\gamma)}{H^2 s^3}$ and $\frac{\dot{M}(s)}{M(s)} = (\gamma-2)O(s^{-1}) = \gamma O(s^{-1})$.

As a result, the contrast variation can be linked to the Lipschitz regularity:

$$\dot{C}(s) = -(1+C(s))\frac{\dot{M}(s)}{M(s)} = -(1+C(s))\gamma O(s^{-1}).$$

Integrating by separation of variables:

$$\int_{C(s_0)}^{C(s)} \frac{\dot{C}(s)}{1+C(s)} dC(s) \propto -\int_{s_0}^{s} \frac{\gamma}{s} ds$$

we achieve: $\ln\left|\frac{1+C(s)}{1+C(s_0)}\right| \propto -\gamma \ln\left|\frac{s}{s_0}\right|$, i.e.

$$\gamma \propto -\ln\left|\frac{1+C(s)}{1+C(s_0)}\right| / \ln\left|\frac{s}{s_0}\right|. \qquad (3)$$

It is worth stressing that the result above allows to give some constraint to choices usually made at hand in literature. First, just two scale levels are required for a correct discrimination between noisy and uncorrupted points of the

[2] $f = O(g)$ means that f has the same order of g.

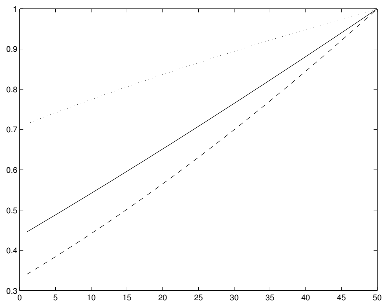

Figure 3: Representative curves of the $z^{\gamma+1}$ correction in the 2^{nd} phase: $\gamma = .5$ dotted, $\gamma = 1.2$ solid and $\gamma = 1.6$ dashed.

Figure 4: Another example of faded print: Arena di Pola.

faded image. Taking into account the point-wise nature of the noise, two levels among all the possible ones can be selected. Furthermore, it does not require any additional threshold for discriminating the nature of each pixel and the corresponding enhancement function. Finally, the size of the context, i.e. $\Omega(s)$ is directly tied to the support of the regularizing function: in our case the mean can be seen as the convolution between the image and a Haar basis function at a given scale. It is obvious that the aforementioned considerations are valid just in case of contrast enhancement under noise and not in general. In the latter case, the parameters above have also to account for the local frequency information of the image.

Coming back to (3), the value of γ can be inserted in a z^{γ} correction. In fact, considering the contrast enhancement curve $z^{1+\gamma}$, we have the effects shown in Fig. 3: a lower enhancement for noisy pixels ($\gamma < 1$) than for good points (having $\gamma > 1$). Moreover, for a greater regularity (greater γs) a stronger enhancement is performed. In other words, the contrast of flat regions is increased, giving the image the vividness characteristic of natural images [14]. On the contrary, edges (lower but still positive γs) are slightly less enhanced, avoiding the halo effect which is common to many contrast enhancement approaches. It is worth highlighting that the aforementioned effects are based on the hypothesis that gray levels of any faded image are located in the right-most part of the x-axis. Summing up, this phase allows to

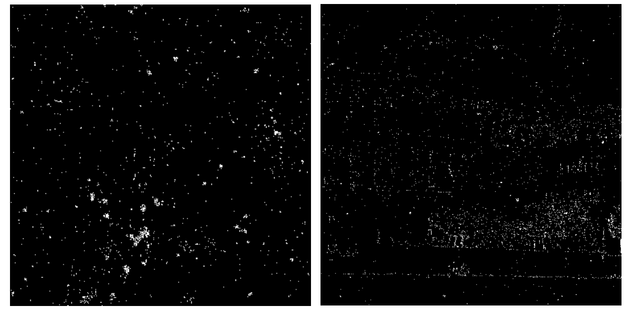

Figure 5: Map of blotches in Fig. 1 (*left*) and Fig. 4 (*right*).

achieve an image that is still faded, but whose pixels have been changed in agreement with their regularity. As a result, the noisy pixels are reduced (emphasized less than other pixels) while contrast of good points is increased accounting for their context.

2.3 Defading and image quality measure

In order to definitely reduce the fading which affects the print, a final operator is applied. It is a global luminance mapping, uniform in the image, based on a z^{α} correction. The luminance mapping depends on the choice of the parameter α. To set its value, we resort to an image quality measure. The distribution of the local standard deviation σ_d with respect to the local average μ_d of the luminance has been used recently in order to define a figure of merit for a restoration algorithm applied to faded images [12]; later it was also shown that such two statistical parameters live constrained in a well defined region of the plane (μ_d, σ_d) [13]. We will use here the same approach, in order to get at least an indication about the optimal values of the parameters used in the algorithm described above.

Let us suppose we can acquire a given real-world scene with an ideal linear device, getting a digital image; consider only its luminance values for simplicity. We subdivide the image in $n \times n$ adjacent blocks, and calculate the standard deviation σ_d and the average μ_d of the gray levels in each block. In the (μ_d, σ_d) plane each block is represented by a point. If we imagine to repeat the procedure for a huge set of scenes with any conceivable contents, and to display the corresponding values in a single (μ_d, σ_d) plane, we will get a cloud of points which shows no correlation between μ_d and σ_d. There is no reason, indeed, why the average luminance of a real-world object of part of an object should influence its s.d.. Notice that this consideration does not contradict Weber's law, which is related to our perception of the scene, and is not a property of the scene itself. The situation is different if, as it happens in practice, the dynamic range of the acquisition device is limited; in this case indeed very dark and very bright blocks will present limited deviation. It can be demonstrated that the range of σ_d values which characterize the blocks acquired with a device yielding output values in a limited range is a bell-shaped function of the average of the block; the function takes its maximum values when the average is half the available range and falls to zero when the average corresponds to the minimum or the maximum of the luminance range [13].

A proper distribution of the points in the (μ_d, σ_d) plane, and more precisely in the bell-shaped area mentioned above, can be taken as an indicator of image quality. In fact, it cannot straightforwardly be used to estimate the quality of an acquired picture in general, because good-looking images exist which do not satisfy this criterion: more indicators are needed. However, it does prove useful when we are dealing with faded photographic prints. This category of images indeed shows a degradation which brings the average luminance values towards the higher portion of the range; hence the corresponding values of σ_d are constrained to be relatively small. The effectiveness of a processing devoted to the enhancement of the digitally acquired version of the print can thus be evaluated based on the improvement in the value of σ_d which is achieved. More specifically, it should be noted that the correlation coefficient between μ_d and σ_d can be estimated via:

$$\rho(\sigma_d,\mu_d) \simeq \frac{\sum_N (\sigma_d-\bar{\sigma_d})(\mu_d-\bar{\mu_d})}{\sqrt{\sum_N (\sigma_d-\bar{\sigma_d})^2}\sqrt{\sum_N (\mu_d-\bar{\mu_d})^2}} \quad . \qquad (4)$$

It tends to assume negative values for the degraded picture; after processing, the shape which the cloud of points in the (μ_d, σ_d) plane takes corresponds to values of ρ closer or equal to zero. This permits to select the processing parameters having this objective criterion as a reference, as done in part three of the proposed method and shown in the following section.

2.4 The Algorithm

Phase 1

- For each pixel $I(x,y)$, compute the contrast matrix $C(x,y,s)$ at a given scale s, as in (1);
- Compute the standard deviation σ of $C(x,y,s)$;
- Hard threshold $C(x,y,s)$ using as threshold value $th = 3\sigma$. Let $B = \{(x,y) : |C(x,y,s)| > th\}$.

Phase 2

- Compute $C(x,y,s_1)$ at another scale level s_1;
- Estimate $\gamma(x,y)$ using (3) if $(x,y) \in B$, else $\gamma(x,y) = 0$;
- γ correct $I(x,y)$ through the function $\tilde{I}(x,y) = I^{\gamma+1}(x,y)$.

Phase 3 Let $\min(\tilde{I})$ and $\max(\tilde{I})$ respectively be the minimum and maximum value of $\tilde{I}$, where the points in B have been neglected. For each $\alpha \in [\alpha_{min}, \alpha_{max}]$:

- stretch $\tilde{I}$ as follows: $(\frac{I-\min(\tilde{I})}{\max(\tilde{I})-\min(\tilde{I})})^{\alpha}$;
- compute ρ_α using (4) and select $\overline{\alpha} = min_\alpha |\rho_\alpha|$;

Then, stretch $\tilde{I}$ using the optimal $\overline{\alpha}$.

3. EXPERIMENTAL RESULTS

The proposed framework has been tested on various images coming from the Fratelli Alinari Archive. In this paper we consider the two images shown in Figs. 1 and 4. They are sepia images so that we will consider in this paper just the contrast enhancement of the luminance component, leaving unchanged the two chroma ones. Both images show evident opaque blotches. Using blocks of 3×3 pixels, i.e. $(H/2)\,s = 1$, as context for computing the local contrast in (1), the maps of blotches achieved in the first phase are shown in Fig. 5. It can be noted that the result is quite satisfactory: it allows to detect almost all the blotches. In the second phase, the estimate of γ requires the computation of the contrast at two different resolutions. Along with the size 3×3 already used in the first phase, a square window of size 15×15 has

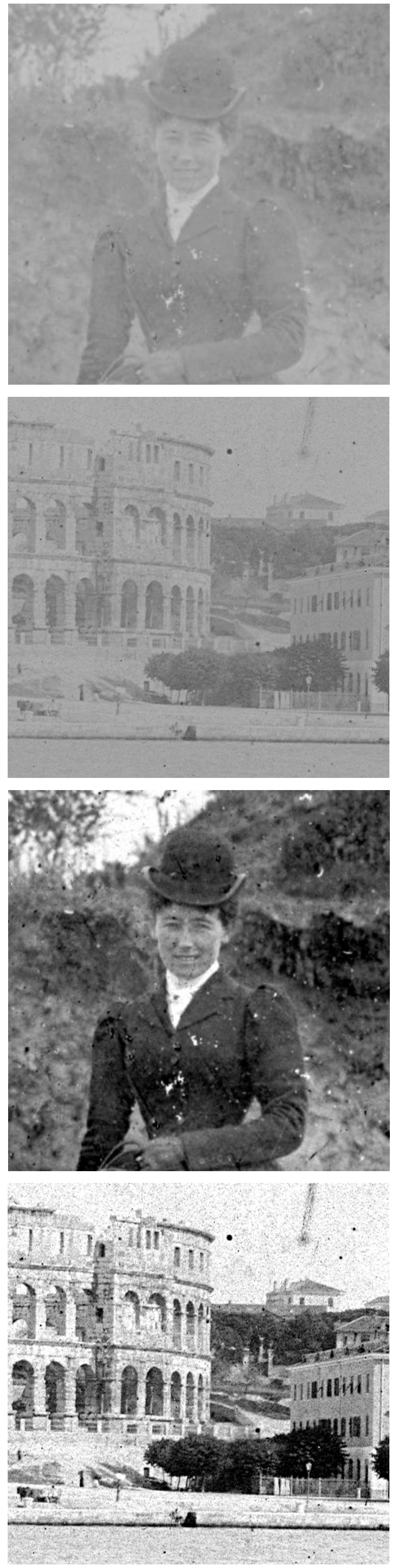

Figure 6: Result after phase 2 *Top* and phase 3 *Bottom*.

been used. It is worth emphasising that very similar values of the corresponding γ are achieved for different choices of the window size. This is encouraging since the estimate of γ in (3) does not consider the constants. Performing the correction through the characteristic curve $z^{1+\gamma}$ we achieve the result in Fig. 6.top. It can be noted that the resulting images are still faded but with a drastic reduction of the noise contribution. The output coming from the second phase is finally enhanced via a z^{α} curve in the third phase. α is a global parameter (one for all image pixels) and in our experiments it assumed the following values $\alpha = 1.1$ and $\alpha = 1.2$. They have been selected in correspondence to $\rho = 0$ since a good correspondence exists with the perceived image quality. The final result is shown in Fig. 6.bottom. All the involved parameters are automatically tuned. In particular, it is true for the adaptive enhancement based on Lipschitz regularity. On the contrary, conventional multiscale methods require the tuning of more than one threshold according to the adopted non linear contrast enhancement function and the allowed level of noise. Fig. 7 shows the enhanced images obtained using the wavelet based method in [16] (*top*) and a simple linear contrast stretching (*bottom*). Neither is satisfactory: in the former noise is still visible, while in the latter highly detailed regions are excessively smoothed.

4. CONCLUSIONS

In this paper we have presented a framework oriented to give the original vividness to faded images. It firstly exploits the link between the local image regularity and the change of contrast for performing an adaptive contrast enhancement. Then, a global γ correction is performed. The proposed model allows a gradual enhancement avoiding drawbacks as halo and noise amplification. Future studies will be oriented to exploit the achieved theoretical results for exploiting the aforementioned link in more sophisticated bases as [15].

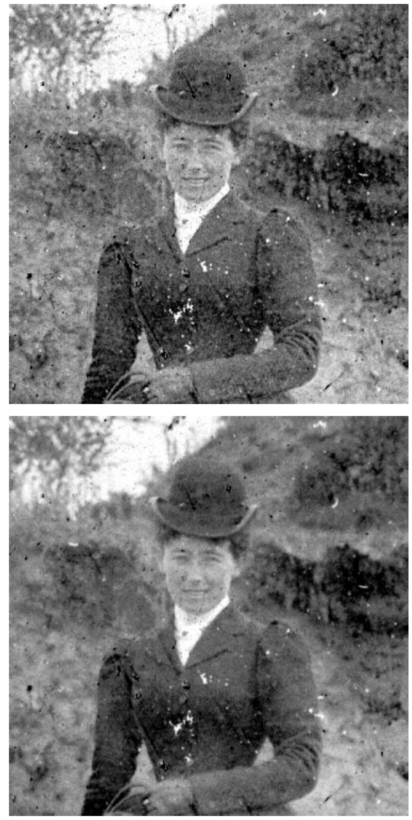

Figure 7: Defaded image using the adaptive multiresolution method in [16] (*top*) and a linear contrast stretching (*bottom*).

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