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VIRTUAL RESTORATION OF FADED PHOTOGRAPHIC PRINTS

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ABSTRACT

Antique photographic prints are subject to fading due to the action of time and of diverse chemical agents. A method for automated virtual restoration of digital images obtained from scanned photographic prints is proposed in this paper. The effects of film grain noise are also taken into consideration. Experimental results on archive photographic material show the performances of the proposed technique.

1. INTRODUCTION

Digital image processing has offered a new way of preserving antique documents like books, manuscripts, photographs, or movies. It provides several advantages:

- it allows their virtual restoration without altering the original artwork;
- it enables to deal with many kinds of defects that sometimes are hard to remove using the classical restoration methods;
- it provides almost automatic restoration tools that can be managed even by inexperienced users.

Degraded documents can be affected by blotches, foxing, fading, cracks, film grain noise, scratches, and so on. Each degradation has a different origin (chemical, physical, mechanical) and appearance [1]. Hence, it is necessary to investigate each defect at a time for providing a really effective restoration technique.

In this paper we deal with faded images. In particular we pay attention to scanned antique photographic prints. They are characterized by a global loss of the vividness of the color, as shown in Figs. 3 and 6. This effect is due to the aging of the print along with the action of some chemical agents which cause its bleaching. Therefore, the degraded image results poorly contrasted.

The problem could be solved by using standard contrast enhancement techniques [2] in order to make the picture span the desired range of values. Unfortunately, the various above mentioned defects alter the range spreading process and can be significantly emphasized. For example, deposited matter, blotches or dust are often composed of groups of dark or very bright pixels. Therefore, they modify the lower and upper pixel values of the image, yielding a poor enhancement result. A blind contrast stretching also causes the amplification of film grain noise; since noise is signal–dependent, nonlinear operations are required for inhibiting its action.

In the following we propose an effective and fast technique for enhancing faded images. Since we deal with faded black-and-white or sepia images, only the luminance component is processed. This approach differs from the one usually followed for faded scanned movies [3], and yields a twofold benefit: the computational load is strongly reduced and, more importantly, the risk of introducing false colors in the processing is minimzed. A Rational Filter (RF) [4] is used for guiding the process. It is a nonlinear, edge–preserving filter, and is able to provide the smooth component of an image without loosing its significant structures. In this way the image is split into its homogeneous and detail components; noise can be found and dealt with in the latter. In the next section the proposed de–fading technique is presented in detail.

Objective measures for evaluating the final result cannot be easily defined. Nonetheless, a de–fading technique has to provide vivid colors, emphasize image details, including the ones that are hardly distinguishable in the faded image, but, at the same time, it has to account for external elements of the actual photograph, such as other damages, that can seriously compromise the final result. In Section 3 some experimental results on real degraded pictures are shown, proving that the aforementioned requirements are accomplished by the proposed approach with a low computational effort. Finally conclusions are drawn in Section 4.

2. THE RESTORATION TECHNIQUE

In the method we describe below, we deal with sepia images and then we leave the color of the image unaltered. The acquired image is converted from the RGB format to a color difference space (we used YCbCr); then the luminance component is processed and finally the two chrominance components are added back, unchanged, to the modified luminance. This of course is not the only possible choice; the user can opt for the visualization of the luminance only of the processed image, discarding the color information. In the experiments section we will show results both with and without the color components.

We may assume that the luminance value y_F of a pixel of the acquired image is represented as

$$y_F = ak + (1-a)h \,, \qquad (1)$$

where k and h, in the faded image, respectively are the minimum reflectance of the (partially oxidized) silver grains and the maximum reflectance of the paper in areas devoid of silver. In an ideal image where the unaltered silver allows for the generation of a deep black, k should be zero; at the other end of the range, if the paper had not been subject to yellowing effects perfect reflectance would cause the generation of white which we represent (in an 8-bit scale) as the ideal value of 255 for h. Fading and yellowing will cause k and h to depart from such ideal values. a, in the range [0,1], determines the fraction of silver grains present in the pixel area which is being scanned.

We first estimate k and h from the image at hand. To this purpose, the most obvious idea would be to take respectively the smallest and largest values of the luminance of the picture, but it should be observed that, as observed above, often photographic prints are affected by other defects; these may alter the outcome of this measure. In particular, deposited matter and dust can be a cause of error. We cope with this problem in a simple way, by assigning to k and h the minimum and maximum values of the image after median filtering. The median filter eliminates small defects while it does not affect important image structures and does not introduce gray levels which do not already belong to the original data; as far as the determination of k and h is concerned, it just permits to shorten the tails of the luminance distribution (especially on the dark side). An example of the histogram of a faded print before filtering is shown in Fig.1; the minimum and maximum luminance are respectively 25 and 204; after median filtering (square support, size 7x7) these extrema become 85 and 191 and are taken as k and h values. We emphasize that the filtered image is created only for this purpose and then it is discarded. Our experiments showed that in general a 7x7 median filter is effective for this purpose; with severely degraded images an automatic method for defect detection, such as the one used in [5] for foxing, should be used to determine the filter size.

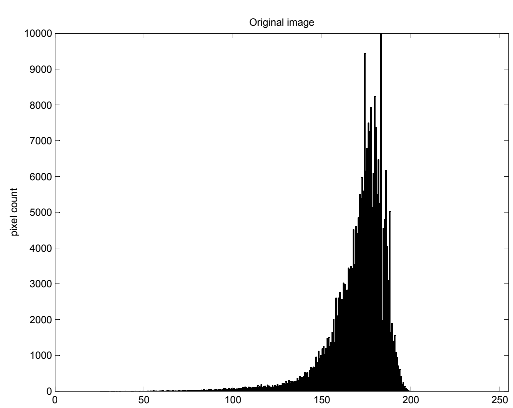

Figure 1: Luminance histogram of a typical faded print.

In order to exploit at best the available dynamic range, the luminance of the faded image should now be expanded to the range [0,255]. Given k and h, for each gray value y_F one could estimate the value of a from Eq.(1): $a = (y_F - h)/(k-h)$, and build the corresponding output level as $y = 255(1-a)$, like in conventional histogram stretching. This approach however would create an annoying amplification of the film grain noise. The method we propose, instead, separates the input image into a smooth component and a differential component, which are treated differently. The smooth term is derived by applying a nonlinear, edge-preserving filter to the input image; the operator we choose is a Rational Filter [4] which can be expressed as

$$y_{rf}(i,j) = y_F(i,j) \quad + \frac{y_F(i-1,j)+y_F(i+1,j)-2y_F(i,j)}{t(y_F(i-1,j)-y_F(i+1,j))^2+5} + \frac{y_F(i,j-1)+y_F(i,j+1)-2y_F(i,j)}{t(y_F(i,j-1)-y_F(i,j+1))^2+5} \qquad (2)$$

here t is a positive parameter that controls the filter: the larger t is, the more the smoothing effect of the filter is reduced in presence of image edges, which are sensed by the quadratic denominator terms in the equation above. The resulting image y_{rf} will still have well-marked large edges, while values inside a region will be made more homogeneous. On this image histogram stretching is performed, which yields the enhanced smooth component

$$y_{rfs} = 255(y_{rf} - k)/(h-k)\ . \qquad (3)$$

The differential component is derived as

$$y_d = y_F - y_{rf}\ , \qquad (4)$$

and must be processed and added back to the enhanced smooth component. Its enhanced version in the most straightforward case should be obtained as

$$y_{ds} = 255 y_d/(h-k)\ . \qquad (5)$$

In this way, the smooth and differential components would be treated in the same way, and adding them together would correspond to perform a stretching of the histogram of the original data. To limit the already mentioned film grain noise effects, it is instead expedient either to apply a smaller amplification factor to the differential component or to perform specific noise smoothing. In the former case, with various experiments we have verified that a good compromise between visibility of the image details and noise attenuation is obtained when the output luminance is expressed as

$$y_{out} = y_{rfs} + \alpha y_d\ , \qquad (6)$$

where

$$\alpha = (255/(h-k))/2\ . \qquad (7)$$

If the image is particularly noisy, it may be convenient to choose the latter course and perform some dedicated processing on the detail image y_d. We exploit the fact that, as it is well-known, film grain noise is a signal-dependent noise, which can be expressed as a multiplicative process in the intensity domain [6]. Hence, the correct approach is to move the y_d data to a logarithmic domain, filter the signal, and take the exponential of the output. This is what we propose to do, with the further improvement of using a nonlinear filter to preserve the small features of the differential signal; we use for this purpose again an RF like the one defined in Eq.(2). It should be noticed that this choice is made only for simplicity; other strategies for the control of multiplicative noise could be used. For example Tekalp and Pavlović [7] propose to operate in a so-called exposure domain where a linear convolution relationship can be established between the ideal and the degraded images; a homomorphic structure results, and a linear minimum mean square error operator is derived. More recently, Yan and Hatzinakos [8] show that for film grain a reliable estimation of the noise model parameters is obtained using higher-order statistics, and propose a new Wiener-type filter based on them. Since photographic images are highly non-Gaussian and film grain noise is nonlinearly related to the original image, filtering schemes based on statistical moments of order larger than two can give better performance.

After the RF application, the processed differential signal y_{df} is added to the enhanced smooth component, similarly to what was indicated in Eq.(6):

$$y_{out} = y_{rfs} + \alpha y_{df} \ , \tag{8}$$

but using now

$$\alpha = 255/(h-k) \ . \tag{9}$$

The final processing step consists in superposing (if desired) the chroma components *Cb* and *Cr* on the modified luminance y_{out}, and convert the result to the conventional RGB format. The block scheme in Fig.2 summarizes the proposed algorithm.

3. EXPERIMENTAL RESULTS

The proposed algorithm has been evaluated by processing a number of faded photographic prints originated from the historical archive of the Fratelli Alinari museum in Florence. Since ideal versions of the processed pictures are of course not available, the quality of the results can be estimated only by visual inspection. We present some results in the following. Fig.3 shows an original image and the images output by various sub-operators: the luminance image processed using the RF, before and after histogram stretching; the detail image (amplified and centered on middle gray for better readability) before and after the RF; finally, the RGB output image. If the sepia tone is undesired, the user can take only the luminance component of the output image, shown in Fig.4. It may be noticed that the image details are well visible, the image dynamics exploit the available range (see also the luminance histograms of the input and output images in Fig.5), and film-grain noise is not disturbing. Scratches and other damage are present in the picture and no attempt is made here to eliminate them; this is not a purpose of this paper, and it has been addressed elsewhere.

Another example is shown in Fig.6. In this case the noise in the original image was negligible, and no filtering was performed in the differential component image; the value of α was set according to Eq.(7).

4. CONCLUSIONS

A method has been proposed in this paper for the automated processing of faded photographic prints, and its validation has been performed via some experiments. Even if no objective figures of merit can be given, the apparent performance of the technique is satisfactory, and the output images show details which are barely recognizable in the input data. Further developments of this technique could deserve attention to the resolution used in the digital acquisition of the print. In the experiments shown above, 300 dpi images have been used: this is the standard resolution used by F.lli Alinari for their archive, but larger figures may be more adequate if the image is used for high size digital prints. The principle of the proposed restoration method is not affected by resolution, but probably the values of some parameters have to be changed accordingly, and further experiments are needed.

Figure 4: Luminance component of the image in Fig.3, after processing with the proposed method.

5. ACKNOWLEDGMENTS

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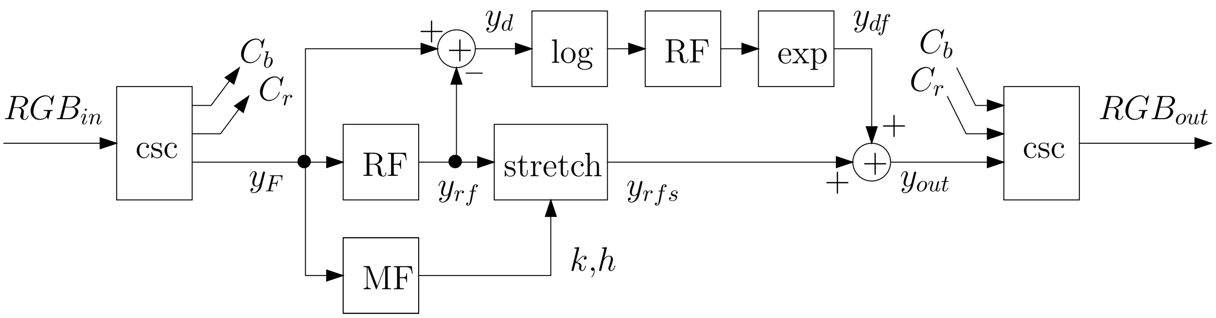

Figure 2: Block scheme of the proposed algorithm (csc: color space conversion; RF: rational filter; MF: median filter).

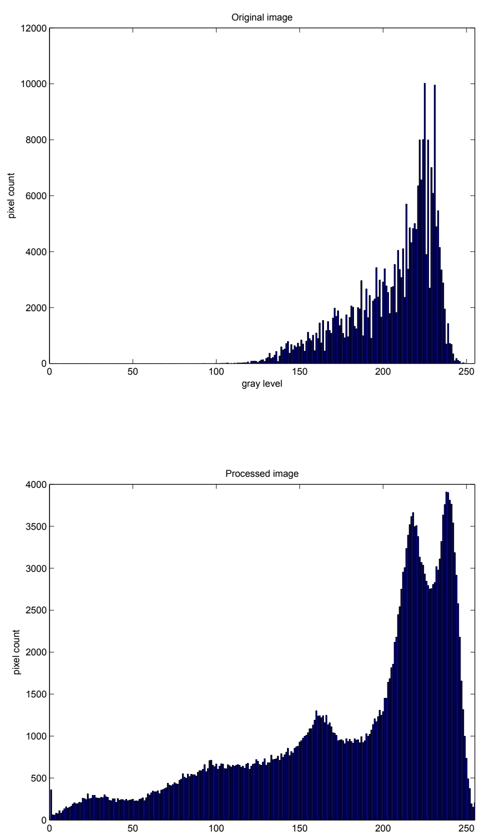

Figure 5: Histograms of the luminance component of the image in Fig.3, before and after processing.

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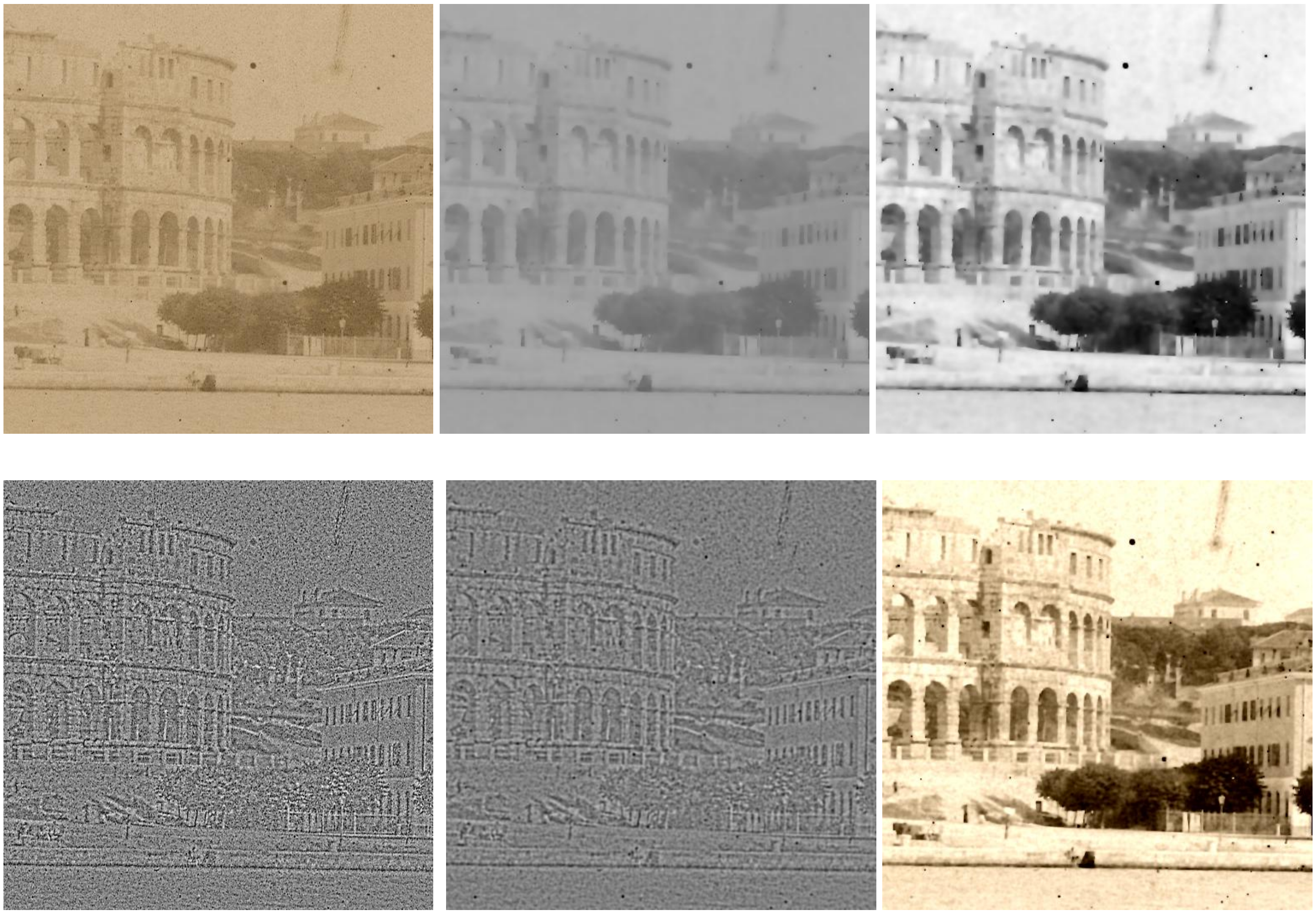

Figure 3: Example of the processing steps. First row: original image, luminance after Rational Filter (y_{rf}), luminance filtered and stretched (y_{rfs}); second row: differential image (y_d), filtered differential image (y_{df}), color output image.

Figure 6: Further example, original (left) and processed (right) images.