VISIBILITY BASED DETECTION AND REMOVAL OF SEMI-TRANSPARENT BLOTCHES ON ARCHIVED DOCUMENTS

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Keywords: Image restoration, ancient documents, visibility laws, semi-transparent blotches.

Abstract: This paper focuses on a novel model for digital suppression of semi-transparent blotches, caused by the contact between water and paper of antique documents. The proposed model is based on laws regulating the human visual system and provides a fast and automatic algorithm both in detection and restoration. Experimental results show the great potentialities of the proposed model in solving also critical situations.

1 INTRODUCTION

Digital restoration provides a new way of preserving and recovering archived documents with non-invasive techniques. In fact, it allows us to give the document its original appearance and to make it more readable and visually pleasing. Digitized documents can be affected by different kinds of damage, which can be classified in two main classes:

- physical and chemical degradation, such as cracks, scratches, holes, added stamps, smeary spots (water or grease), foxing, warping, bleed-through and so on — see for instance (Tonazzini et al., 2004; Stanco et al., 2003; Brown and Seales, 2004) and references therein;
- damages which are caused during the conversion of the document in its digital format, such as scanning defects, show-through, uneven background and so on — see for instance (Shi and Govindaraju, 2004; Sharma, 2001).

A lot of research work has been done for trying to solve one or more of the aforementioned problems. In fact, each defect can be processed using a specific and oriented strategy or employing integrated environments that are able to select the best restoration technique for it (Cannon et al., 2003). Moreover, a really useful approach needs a low computational effort and user's independence.

In this paper we deal with semi-transparent blotches. They are common defects on ancient documents and are caused by the contact between paper and water. They usually appear as irregular regions with darker intensity with respect to the original paper. The detection phase is very delicate. In fact, the geometric shape of the degradation is not significant since it changes from a blotch to another also in the same image. It is the same for both color and degree of transparency. On the other hand, their removal is critical whenever they involve characters. We assume that the image we wish to restore is composed of characters which are darker than their background. In this case the darkness of the background can approach the one of the text, making the discrimination between the two objects somewhat difficult. Fig. 1 shows three successive steps in the evolution process of humidity damage. In the first case, water has been in contact with the paper for a limited time and the damage is only slight. In the second case, the time of contact has been longer and the resulting damage is more evident. Finally, in the third case, after long term humidity, the effects are drastic causing significant damage to characters information. Hence, the goal of a recovering algorithm consists of enhancing the text but, at the same time, restoring the background without altering its artistic features like color, textures and eventual drawings and pictures.

With regard to text segmentation, a lot of work has been done, since it corresponds to a sort of text binarization (Valverde and Grigat, 2000; Oguro et al., 1997) which is a common problem in faxed or table form document — not necessarily ancient. It is often solved by using global (Solihin and Leedham, 1999) or adaptive thresholds (Hwang and Chang, 1998;

Bruni V., Crawford A., Vitulano D. and Stanco F. (2006).
VISIBILITY BASED DETECTION AND REMOVAL OF SEMI-TRANSPARENT BLOTCHES ON ARCHIVED DOCUMENTS.
In *Proceedings of the First International Conference on Computer Vision Theory and Applications*, pages 64-71
DOI: 10.5220/0001371700640071

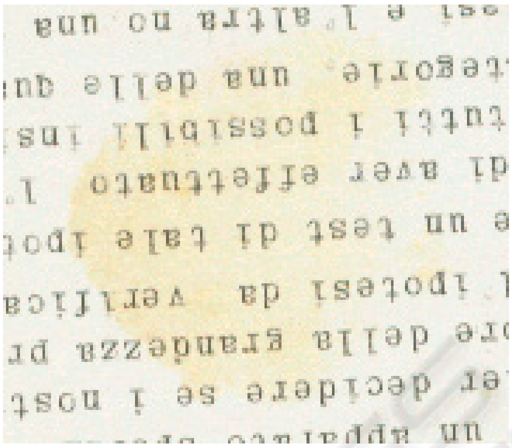
Yang and Yan, 2000). The threshold requires some assumptions on the characters, the background or the defect like width, frequency content and uniform color — an interesting comparison between thresholding based approaches is in (Leedham et al., 2002). On the other hand, linear and non linear methods are also proposed. They use some prior probability models for establishing the nature of a pixel (*foreground* or *background*) (Zheng and Kanungo, 2001; Huggett and Fitzgerald, 1995) or multispectral acquisitions for better distinguishing between background and text, whenever their intensities assume very close values (Tonazzini et al., 2004). Nonetheless, they are constrained by the width of the characters, as in (Huggett and Fitzgerald, 1995) or they assume the mixture problem linear, see for instance (Tonazzini et al., 2004). Mathematical morphology is also widely used for a further step of text restoration.

Moreover, binarization and text enhancement techniques do not include the restoration of the background, which is assumed uniform. Some recent works try to locally model the background with planes (Shi and Govindaraju, 2004) or using multispectral acquisition (Easton et al., 2004), but they result computationally expensive. An attempt to automatize the process using very simple operations is in (Ramponi et al., 2005). In this case, the text is distinguished from the rest by means of Otsu threshold while the degradation is detected by means of its color. A rational filter (RF) and a merging operation are then used in the restoration step. Nonetheless, it is almost insensitive to slight changes of the intensity values and then it is not successful for highly degraded text.

In this paper, the proposed model simulates human perception for detecting blotches while it uses visibility laws (Foley, 1994; Hontsch and Karam, 2000) for removing them. It represents a first attempt to introduce the laws regulating the human visual system (HVS) in the restoration of text documents and shows great potentialities also in critical cases.

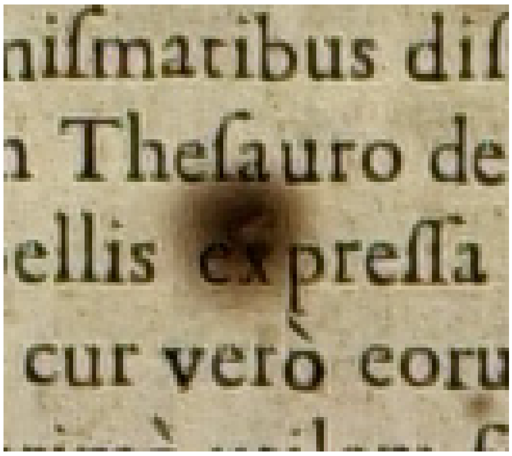
In fact, visibility laws enable the enhancement of the text and, at the same time, allow us to also recover the structure of the background, i.e. irregularities, textures and color, thanks to the simultaneous measure of local and global features of the image. These properties make the algorithm completely automatic since visibility parameters are independently estimated on the image under study. In that way the model results completely independent of thresholds to be tuned, differently from binarization strategies, and it is able to automatically adapt to images with different size and resolution.

In the detection step, the same process employed by the human visual system at a low level of attention (Gonzalez and Woods, 2002; Hontsch and Karam, 2000) is performed. It consists of a low pass filtering of the image oriented to extract the regions of the im-



(a)

(b)



(c)

Figure 1: (a) Slight semi-transparent blotch; (b) dark semi-transparent blotch where the text is visible; (c) dark semi-transparent blotch where not all the text is visible.

age containing semi transparent blotches. On the contrary, the restoration exploits the transparency of the defect by reducing its intensity under the level of human visual perception. The attenuation is balanced by local and global measures of the perception for each degraded pixels. The philosophy adopted in this paper is pretty similar to the de-scratching of archived films in (Bruni and Vitulano, 2004; Bruni et al., 2004) since also semi-transparent blotches cover without completely removing original image information.

The outline of the paper is the following. Section 2 presents a novel model for both detection and restoration of semi-transparent blotches and briefly explains the human perception laws that guide both phases. Some experimental results and discussions are respectively contained in Sections 3 and 4.

2 THE PROPOSED MODEL

As mentioned in the Introduction, the detection of semi-transparent blotches is not a trivial problem since the degradation cannot be formally modelled. In other words, we don't know exactly what we are looking for. In fact, the shape of the degradation changes from one image to another and in the same paper we can find completely different blotches. This fact depends on the porosity of the paper, the degree of humidity and also the time of the contact between the water and the paper. Therefore, it is difficult to automatically separate the blotch from the remaining part of the document, even using multistage thresholding strategy (Shi and Govindaraju, 2004). Nonetheless, the Human Visual System (HVS) is able to detect blotches at the first glance and to distinguish it from the remaining components of the scene (background and text in this case). In the following subsection, we will show how it is possible to select degraded regions by modelling HVS using a guided low pass filtering operation. A binary mask is the output of the detection phase. The mask is a lookup table for the regions of the paper which are affected by the degradation. These regions do not contain only blotch but also non uniform background and text. Moreover, since the blotch is semitransparent, these components are not completely damaged (see Fig. 1). Therefore, the restoration consists of separating the blotch from the text and attenuating blotch intensity, accounting for some visibility constraints, i.e. *contrast sensitivity* and *contrast masking* (Hontsch and Karam, 2000; Foley, 1994). *Contrast sensitivity* measures the visibility of each component of the degraded area with respect to a uniform background. *Contrast masking* is the visibility of an object (*target*) with respect to another one (*masker*) (page 28 of (Winkler, 2005)). In our case the target is the pixel to be restored while the masker is composed of the neighbouring pixels. The aim of the restoration phase is to reduce the intensity of the blotch till it is no longer visible and without creating artifacts in the image, as deeply shown in Section 2.2. In fact, blotches hide without completely destroying the underlying original information, as shown in Fig. 1.

The RGB components of the image to be restored are converted in the YCbCr space (Gonzalez and Woods, 2002). In fact, it is proven that human eye is more sensitive to changes in the luminance component (Y) rather than in the chrominance ones (C_b, C_r) (Mojsilovic et al., 1999). Hence, the algorithm of detection will act directly on Y (luminance) component, while restoration is performed on all three components. Both phases will be analysed in depth in the following subsections.

2.1 Detection

HVS detects blotches at a low level of attention, i.e. during the coarsest step of the analysis of the scene under study. This situation can be simulated by performing a low pass filtering of the image. In fact, blurring gives an image with homogeneous regions in colour, where the blotch becomes darker with respect to the background while the text disappears since mainly characterized by high frequencies (see Fig. 2a). More precisely, the luminance component Y_0 of the degraded image is embedded in a family of images Y_r which are defined as follows:

$$Y_r = Y_0 * H_r,$$

where r indicates the resolution and H_r is a low pass filter whose support depends on r. Then, the problem consists of finding the right level of resolution $\overline{r}$, in which it is possible to automatically extract the blotch with a simple binarization (see Fig. 2b). The level of resolution is set to be the point which realizes a good separation between the main image components in the rate-distortion curve. This latter is used in signal compression and it correlates the number of bits used for coding a given signal versus the error for the corresponding approximation (Gonzalez and Woods, 2002). Here, rate is taken as the resolution of our image, since it indicates the quantity of information. The distortion is measured via the number of lost bins — i.e. zero bins of the image histogram.

Figs. 2c and 2d show that the blurring effect corresponds to a regularization of the histogram of the luminance component. It consists of a reduction of its admissible values in a continuous manner. However, this reduction is not proportional to the level of the blurring but it is faster for smaller levels, slowing as the blurring increases. The Occam filter strategy as in (Natarajan, 1995) can be applied to achieve the best

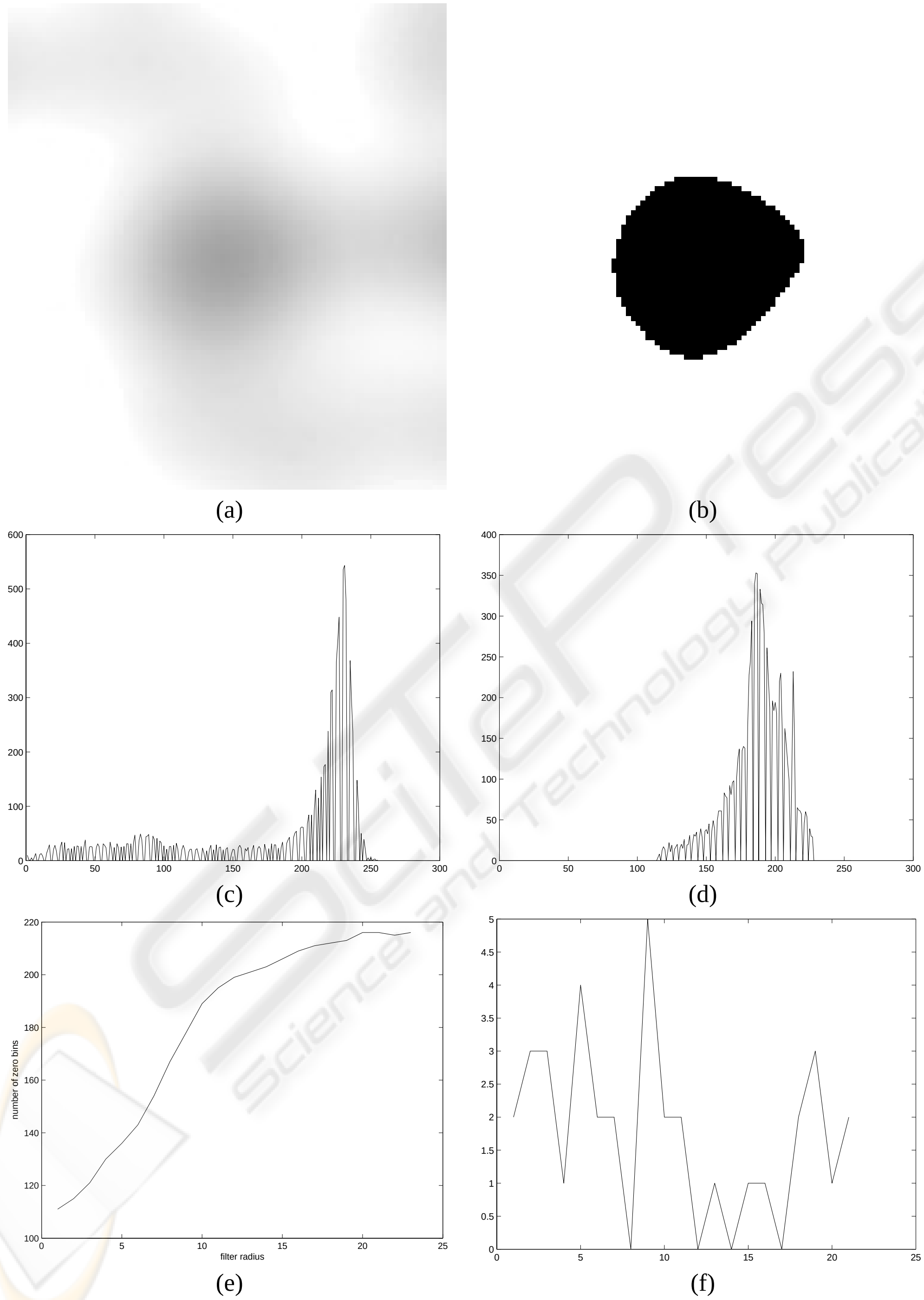


Figure 2: **Top)** Blurred paper with a semi-transparent blotch (a); its corresponding mask (b). **Middle)** Original image histogram (c); blurred image histogram (d). **Bottom)** The level of the optimum blurring has been automatically selected using an Occam filter based strategy, i.e. selecting the maximum ($\overline{r} = 10$) of the discrete second derivative (f) of the rate-distortion curve (e) in the left (see text for details).

level of blurring, i.e. the trade-off between regularization and the number of significant components of the scene. More precisely, we construct the curve of the number of zero bins of the histogram function versus the level of blurring, as depicted in Fig. 2c, and we get the modulus maximum of its second derivative, i.e. the point having the greatest change of curvature (see Fig. 2f). Hence, $\forall\ r \in \mathbf{R}^+$, let $\Gamma_r = g(r)$ the number of zero bins of the histogram of Y_r, hence

$$\bar{r} :\ max_{r\in\mathbf{R}^+}\left|\frac{\partial^2}{\partial r^2}g(r)\right| = \left[\left|\frac{\partial^2}{\partial r^2}g(r)\right|\right]_{r=\bar{r}}.$$

It is worth noticing that in the experiments r is a discrete variable and then also the second derivative must be discretized.

If H_r is a gaussian function, the resolution r will correspond to the radius of the filter.

The final mask will be then the quantized (2 levels) and binarized blurred image, as shown in Fig. 2b. Hence, the output of the detection phase is

$$\cup_{i=1}^{K} B_i = \{(x,y) \in \mathbf{R}^2 :\ |Y_{\bar{r}}(x,y)| > T\},$$

where T is the mean value of $Y_{\bar{r}}$, B_i is the i^{th} blotch and K is the number of non intersecting detected blotches.

2.2 Restoration

From the detection phase, we achieve the region of the blotch B. We assume that it could contain text that must be preserved and eventually recovered. We also assume that the text is darker than the background but it is also possible to consider the symmetric case. According to the visibility laws, we perform our algorithm along image rows and then along columns. In fact, it is well known that the human visual system has a preferential sensitiveness to these two orientations (Hontsch and Karam, 2000). The restored image will be the combination of the results achieved in both directions. From now on, we will consider a row of the luminance component of the image.

Three different kinds of information can be distinguished in a row of the image intersecting the region B: text, blotch and background (see Fig. 3). Text is the darkest component and it is represented by minima in the signal of Fig. 3. The first phase of the restoration process consists of discarding text from the remaining components of B with respect to a perception based threshold: characters will correspond to those minima in the analyzed signal whose energy exceeds the minimum energy value for a perceivable pixel. From now on we will indicate with M the set of minima of the row signal while N will represent the set of maxima. Hence, the energy E_k of each candidate minimum M_k is defined as the area of the triangle whose vertices are M_k and its adjacent maxima N_k^l and N_k^r[1] (see Fig. 3).

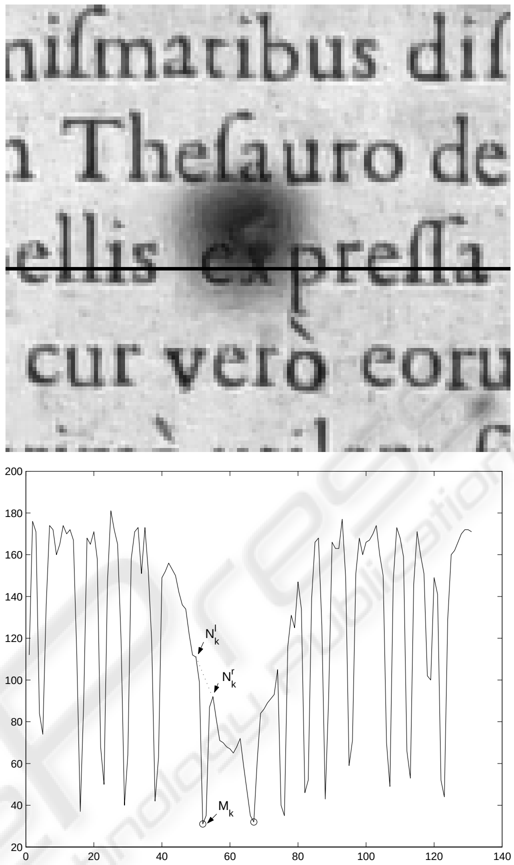


Figure 3: Row no. 69 of Fig 1c. intersecting the detected region. The lowest minima correspond to the text while the envelope of maxima outside the degraded region gives a good estimation of the background.

On the other hand, the energy for a just perceivable pixel is

$$E_m = \frac{1}{2}\Delta f \Delta x,$$

where Δf is the minimum detection threshold (Hontsch and Karam, 2000) and Δx is the average of the distance between two maxima points. The minimum detection threshold is computed with respect to the background f. It represents the least perceivable difference of luminance values between two subsequent pixels. It can be computed from the *Weber's law* (Gonzalez and Woods, 2002), i.e.

[1]Subscript indicates the associated minimum while superscript indicates the position (left or right) with respect to it.

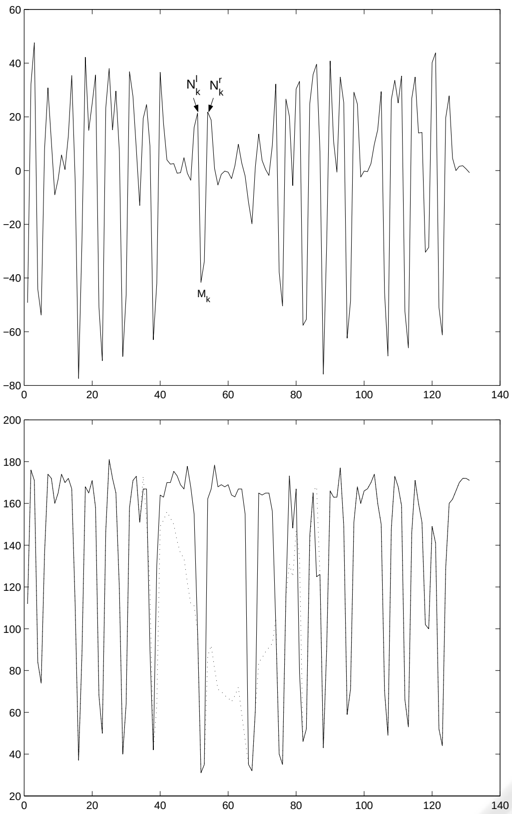


Figure 4: *Top)* Cross section of the row in Fig. 3. *Bottom)* Degraded (*dotted*) and restored row using the proposed method (*solid*). The restoration phase suitably increases the value of pixels between text components, leaving minima corresponding to the text unchanged.

$$\frac{\Delta f}{f} = c \tag{1}$$

where $c = 0.02$. The latter gives the minimum perceivable difference of luminance values between uniform objects. In this work we compute the background value f as the average of maxima points that are not included in the blotch region, since it is assumed to be the lighter component of the image.

In order to improve text discrimination, the same energy based analysis is performed on the *cross section* of the analysed signal. The *cross section* corresponds to the correction of each pixel value with its local mean. Hence, it can be considered a high pass filter, which tries to enhance text high frequencies (see Fig. 4). The number of taps of the filter is the peak of the histogram of the distance between adjacent extrema points in the original signal.

Let $\mathcal{T} = \{(x,y) \in B : Y(x,y) \text{ is text}\}$. Once the text is extracted, the remaining pixels $\{Y(x,y)\}_{(x,y)\in B-\mathcal{T}}$ of the blotch are attenuated according to their importance in the scene. In other words, each $Y(x,y)$ is attenuated measuring its visibility with respect to the image background (*contrast sensitivity*) and its neighbouring pixels (*contrast masking*). The attenuation coefficient γ_{cs} corresponding to the *contrast sensitivity* is computed from the *Weber's law* (1) as follows

$$\gamma_{cs}(x,y) = \frac{f - Y(x,y)}{Y(x,y)}, \quad \forall\ (x,y) \in B - \mathcal{T}.$$

The attenuation coefficient $\gamma_{cm}(x,y)$ measuring the *contrast masking* can be computed similarly. In this case, the background value f in the *Weber's law* is substituted for the intensity value of the adjacent pixel of $Y(x,y)$. The final restoration coefficient $\gamma(x,y)$ can be then written as

$$\gamma(x,y) = 1+\gamma_{cm}(x,y)+\gamma_{cs}(x,y),\ \forall (x,y) \in B-\mathcal{T}.$$

As a matter of facts, it corresponds to an amplification coefficient of the luminance value since the aim of restoration is the lightning of the blotch while the original degraded signal is not zero mean. Hence, the restored pixel $\tilde{Y}(x,y)$ is given by

$$\tilde{Y}(x,y) = \gamma Y(x,y), \quad \forall\ (x,y) \in B - \mathcal{T}.$$

The restored row in Fig. 3 is depicted in Fig. 4. It is worth stressing that γ_{cs} tries to approach the restored pixel value to the background, while γ_{cm} regulates the relationship between subsequent pixels and then preserves the local image texture.

For the chrominance components C_b and C_r, a mean value of the color associated to the background is substituted for the degraded one.

3 SOME EXPERIMENTAL RESULTS

The proposed model has been tested on scanned copies of real antique documents. Over 50 images have been processed having different size and scanned at 300 dpi. They have been kindly supplied by Istituto per le Applicazioni del Calcolo and Biblion Centro Studi sul Libro Antico Onlus. Since their original clean version is unknown, there are not objective measures for evaluating the final result, like MSE or similar. This fact emphasizes the importance of the use of visibility laws in both detection and restoration phases. A successful restoration tool has to hide the degradation without introducing artifacts, i.e. without changing both local and global content of the scene.

In Figs. 5 some results achieved on selected test images are shown. Original degraded images are depicted in Figs. 1b and 1c. They are representative of two different stages of the degradation. In the first case (topmost) the blotch has altered the image but the text is quite distinguishable. The bottommost figure represents a difficult case of study, since the colour of the blotch approaches that of the text. Notice that the letters **e** and **x** are almost completely covered by humidity in their topmost part, as shown in Fig. 1c. Nonetheless, the proposed algorithm is able to recover them thanks to its analysis of the local visibility of a given object. In particular, it is worth noticing the detection and restoration of the letter **x**.

In order to further stress that the algorithm for detecting blotch regions results very effective as well as fast and simple, since based on a global contrast measure of the whole scene, another example is shown in Fig. 6. Also in this case, the critical case represented by the bottommost blotch is detected by the proposed framework.

4 CONCLUSIONS

In this paper we have proposed a novel model for detecting and restoring semi-transparent blotches on archived documents. The model is based on the perception laws regulating the human visual system. The algorithm is very fast and completely automatic both in detection and restoration, under the assumption that text is darker than the background or viceversa. In fact, it performs very simple operations on the degraded area without requiring user's settings. This allows the model to be completely independent of the user making it manageable also by non expert operators.

Future research will be oriented to enlarge the cases of study trying to build visibility based filters (operators), able to model the different appearance of humidity degradation.

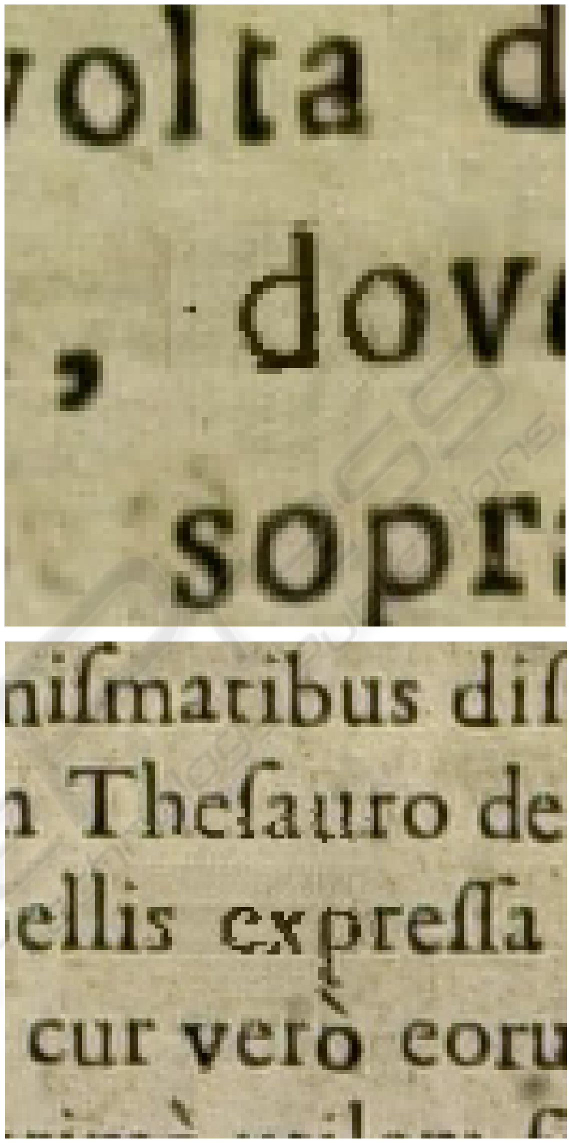


Figure 5: Restored images in Fig. 1b and Fig. 1c using the proposed algorithm.

ACKNOWLEDGEMENTS

We wish to thank Digital Codex and Biblion Centro Studi sul Libro Antico Onlus for providing some of the pictures used in the experiments. The original documents belong to M. Picone Archive of Istituto per le Applicazioni del Calcolo (CNR) in Rome and Redentoristi Library at S. Maria della Consolazione in Venice, Italy. This work has been partially supported by the project FIRB (RBNE039LLC).

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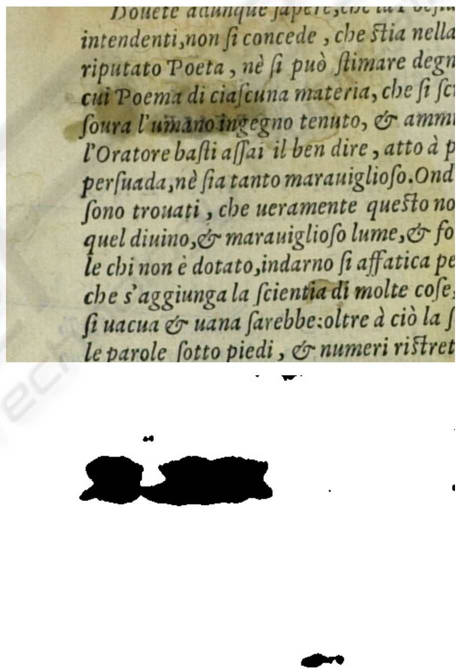

Figure 6: **Top**) Original image. **Bottom**) Detected blotches (black regions) using the algorithm in section 2.1 and $\overline{r} = 12$.