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A SET OF LOW-LEVEL DESCRIPTORS FOR IMAGES AFFECTED BY FOXING

E. Ardizzone, H. Dindo, G. Mazzola

Dipartimento di Ingegneria Informatica (DINFO), Università degli Studi di Palermo
Viale delle Scienze building 6, 90128, Palermo, Italy
phone: +390917028521, fax: + 390916598043,
ardizzon@unipa.it, dindo@csai.unipa.it, mazzola@csai.unipa.it
web: http://www.dinfo.unipa.it

ABSTRACT

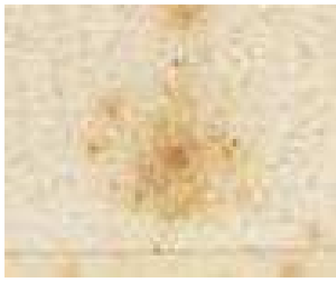
Old printed photos are affected by several typical damages, due to age and bad preservation. "Foxing" defects look like red-brownish spots onto the paper of the printed photo. Similar features can be seen in the digitized copies. In this paper we propose a set of low level descriptors to extract features from digitized photos affected by foxing. An image retrieval application, based on information extracted by the proposed descriptors, is developed to discriminate, through comparison, if an image is affected by foxing. Results are compared to those obtained using some standard color descriptors.

1. INTRODUCTION AND RELATED WORKS

The art of photography is more than 150 years old, but it absorbed quickly technological innovations of the following years. Methods, cameras, techniques changed and improved, and so supports changed, from physical (e.g. paper) to digital ones. Even if the discussion about advantages and disadvantages of digital and film cameras is still open, the need for digital preservation of old documents became more and more pressing. Their economic worth and high cultural value induced the use of digital techniques to protect and preserve them. Old photographic prints may present several types of defects, due to several factors. In most cases, damages are originated by an inaccurate handling and/or store of the original image, or by chemical factors, or by decomposition of the support caused by age[2]. While the knowledge of the causes of degradation is important for the defect analysis on the physical support, different defects may look similar once the document had been digitized. Manual annotation of the damage cannot be a solution. It is expensive and time consuming, because of the typical huge amount of data to be analyzed. Automatic or semiautomatic methods are needed to help in this task.

Several works rely on the analysis of damages in old documents through the study of their digital copies. The works of Abras et al [1] deals with feature extraction for defects such cracks or craquelures in paintings. The Presto-Space project[8] focused on the analysis and removal of defects for the preservation of audiovisual collections. For a complete overview of the existing works in the field of content-based image retrieval see Smeulders et al [6].

(a)



(b)

(c)

Fig.1 Some examples of images affected by foxing. In Fig. 1.b it can be easily observed both the darker kernel of the foxing spot and the lighter surrounding area. (Courtesy of Alinari Archive)

In this paper we will focus on a specific damage of printed photos, the "foxing" spots. The purpose of this paper is to present a set of features for the content analysis of digitized photos affected by foxing. An image retrieval application, based on the extracted features, is proposed to discriminate whether an image is affected by foxing or not.

2. FOXING SPOTS

Foxing is a typical chemical damage which can be seen in old books, documents, postage stamps, and so forth. The term "foxing" was used for the first time in the 18th century, to indicate those red-brown (the color of the fox fur) spots in the surface of the paper of old documents. Actually causes are not clean. Two are the most reliable theories about the chemical origin of these spots[3]. One is that spots are caused by the growth of some fungoid microorganisms on the surface of the paper. Other one asserts that foxing would be caused by the oxidation of iron, cop or other substances

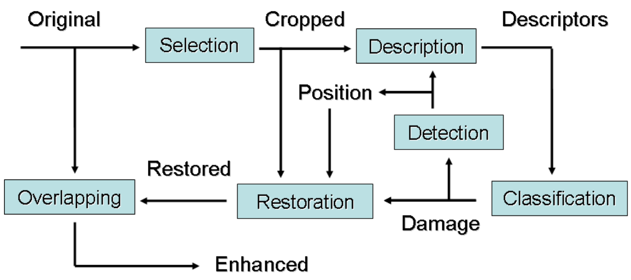


Fig.2 Our restoration model

of which the photographic support is made. Probably multiple factors are involved. Foxing spots are composed by a dark red-brown kernel, surrounded by an area into which colors are smoothed (see fig. 1 for some examples). Information in the center of the spot is totally damaged and must be considered lost. Surrounding area can have some residual information, that could be enhanced with manual or digital techniques. However a discussion about the restoration techniques for documents affected by foxing is out of the scope of this paper.

3. OUR RESTORATION PROCESS MODEL

Damage analysis is one of the most important steps in a restoration process. In this section we briefly describe the model we adopted for the process, to better explain which are the contributes of this work. We need a specific approach to handle defects coming form the digitization of old photos, which are in most case local defects due to the degradation of part of the support of the photo.

Fig. 2 shows a simplified scheme of the model:

- Original image is the whole input image.
- User selects an area of the image, the cropped image, which he recognized as damaged, with no knowledge about the typology of that damage. Cropped image can coincide with the original image for global defects (e.g. fading).
- Selected portion of the image is described by some descriptors, which values are input for a Classification Box.
- The classifier identifies by which type of damage the cropped image is affected, using information extracted by the description step.
- Once the damage has been classified, the appropriate detection method is applied, to locate the position of the damaged pixels into the cropped image. Detection algorithms are also used to support the description step. Detection is by-passed if a global damage has to be processed.
- Since we know the damage, and where damaged pixels are, the proper restoration algorithm can be applied.
- The restored (cropped) image is overlapped with the original image, to reconstruct the enhanced image.

In this paper we focus on the description and the classification step, starting from an existing detection algorithm. Detection algorithms are used to locate damaged pixels in an image which is affected by a specific damage. But they have some limitations, and sometimes wrong information is extracted, if they are applied to images which are not affected that damage.

(a)

(b)

(c)

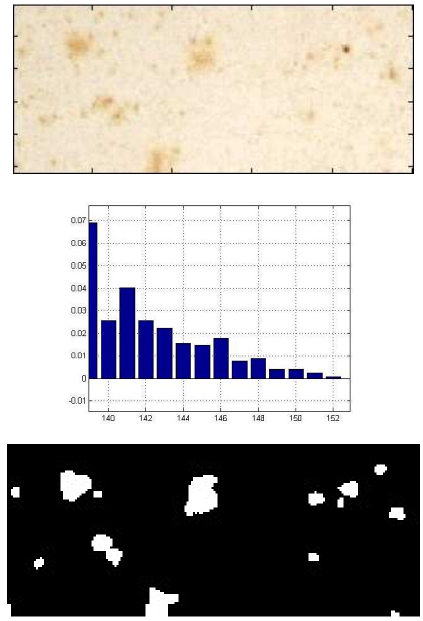


Fig.3 a) Image affected by foxing spots. b) histogram of the Cr chrominance (zoom on the tail). c) detected damaged area.

The proposed description/classification method is used to give an interpretation to this information, in order to discriminate whether an image is affected by that damage or not. Obviously this will be as much complex as the number of the defect types actually considered grows.

4. FOXING DETECTION

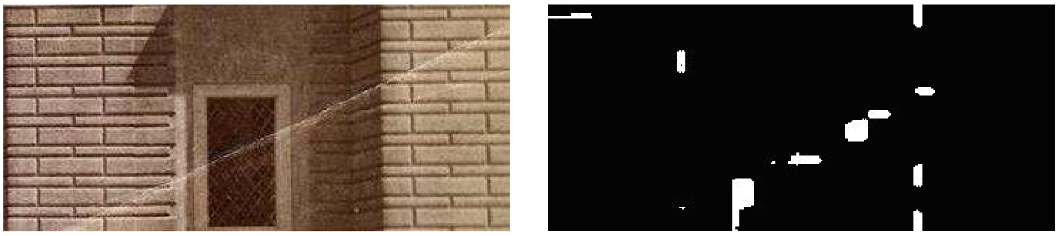
Digital acquisition of an image implies the acquisition of the defects of which the image is affected. In a digital image, defect detection means the ability to locate the position of damaged pixels. In this section we briefly present the foxing detection algorithm proposed by Stanco et al.[7] which will be used in the feature extraction process.

Due to the particular nature of the foxing defect, this algorithm is based on color of the spots, and its distribution.

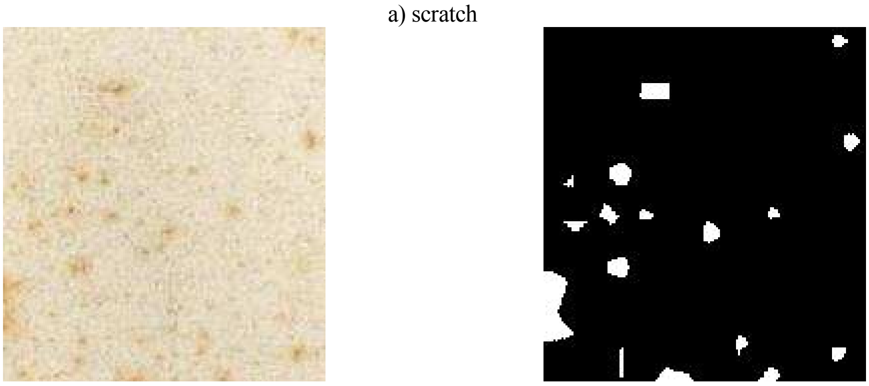
The algorithm works in two steps:

- image is decomposed in the YC_bC_r color space and only the C_r chrominance is processed. It has been shown that C_r histogram of foxed images presents a tail on the right, formed by a set of bins having almost the same small height, and with the peak on the left. The bins on the right tail represent the points damaged by foxing.
- finding all the pixels where the original information is only partially affected by foxing. They are characterized by a lighter coloring than the center of the foxing and their position is near the reddish-brown spot.

Fig. 3 shows an image affected by foxing, the corresponding tail in the C_r histogram, and the detected mask using the described algorithm. We noted that even if it works very well in locating damaged pixels in images affected by foxing, it may sometimes detect small foxed areas in non-foxed images. Figg. 4.a and 4.b show other two examples: in the first case the algorithm correctly detects foxed pixels in a slightly damaged image; in the second case it is applied to a non-foxed image and it wrongly detects a foxed area.



a) scratch



b) foxing (light damage)

Fig.4 a) Image affected by scratch and the corresponding output mask. b) image slightly damaged by foxing and the corresponding output mask.

Comparing the two examples we noted that the two output masks are very similar, so that the described algorithm cannot be used as a classification method. Extracted information needs to be further analyzed.

5. FEATURE EXTRACTION

For an automated application for the analysis and the inspection of an image, some local and global information must be extracted. That is, we must extract some meta-data from the image, which will be used by some specific operators to analyze the image content. "Descriptor" is the representation of one or more features of an image. The MPEG-7 standard proposed[5] a set of descriptors (color, texture, shape, motion, etc.) to formalize the content of multimedia data. The definition of new descriptors for a specific damage of an image can be functional for the development of damage oriented applications (restoration, classification, etc.).

For foxing description, the choice of the best set of descriptors must depend on two aspects:

- the specific features of the foxing spots (color and its distribution);
- the definition of relevant distance metrics, designed for an image retrieval application.

In this paper we focus on three different set of features, to describe a digital foxing spot: the C_r chrominance histogram, the statistical values of the damaged pixels, and the spot size. Each of these elements is used to analyze a specific aspect of the spot.

The first proposed descriptor is the tail of the C_r chrominance histogram, detected as described in section 4 (see fig. 3.b). Bins and heights of the histogram, from the right to the left of the tail, are stored,

$$d_1 = \{(B_i, h(B_i)) | B_i \geq B_l\} \qquad i = 1...256 \qquad (1)$$

where B_i are the bins of the histogram, $h(B_i)$, the corresponding heights and B_l the left value of the tail. This descriptor gives us information about the length, the minimum value, and the distribution of the heights of the tail. That is information about the shade of the color of the spot.

The second proposed descriptor is a set of statistical values of the Cr chrominance component: mean, variance, minimum and maximum value. Values are computed only into the damaged area, detected with the algorithm described in section 4 (see fig. 3.c).

The third descriptor is based on the average size of the spots. This is computed by considering the ratio of the number of damaged pixels in the detected area to the number of the distinguishable spots, located with a 8-connection labelling process(see fig. 3.c).

The next section presents an image retrieval application, based on the information extracted by these descriptors.

6. CONTENT-BASED FOXING RETRIEVAL

A content-based image retrieval (CBIR) application deals with the problem of searching for digital images in a large database. Content-based means that image retrieval is made using information that can be extracted from the image itself, rather than using tags, keywords or annotations by hand.

The goal of the proposed CBIR is to discriminate if an image is affected by foxing. That is, given a new image, we compare its content to that of all the images in the dataset. If the most similar image, according to some distance metrics, is affected by foxing, the new image can be reasonably supposed to be "foxed". In this section we presents three different metrics, based on the proposed descriptors.

The first one is based on the histogram tail descriptor. It is obtained as the difference, point to point, of the heights of the corresponding bins of the tails. Since tails can have different supports, starting and ending point, that with the lower

Table 1. Experimental results

results\distance		HIST	STAT	SIZE	3-STEP	CCV	DC	CS
Correct classification(%)		84,3	87,6	71,4	90,3	88,5	89,4	81,6
False positives(%)		8,3	6,4	13,4	5,1	7,4	5,1	9,2
False negatives(%)		7,4	6	15,2	4,6	4,1	5,5	9,2
Avg exec time (s)	feat extract	1,3				3,9	3,7	9,1
	matching	0,1	<0,1	<0,1	0,1			

maximum is shifted rightward to align the two maxima, and that with the shorter support is zero-padded to have the same support of the other one. Given d_1^1 and d_1^2, the descriptors of the two different tails, supposed d_1^1 to have a maximum value n-units higher than that of d_1^2, the distance of the two tails is:

$$D_1\left(d_1^1, d_1^2\right) = \sum_{B_i=B_{\min}}^{B_{\max}} \left|h(B_{i-n}^1) - h(B_i^2)\right| \qquad (2)$$

where B_{min} is the lowest of the two minima and B_{max} is the highest of the two maximum bins. This distance is used to compare information about the different "trends" of the color in the two images (only damaged pixels), regardless of their absolute values.

The second proposed metric is based on the statistical values of the damaged pixels. It is obtained as the sum of the absolute differences of the corresponding components of the statistical descriptors in the two images:

$$\begin{aligned} D_2\left(d_2^1, d_2^2\right) = &\left|d_2^{1mean} - d_2^{2mean}\right| + \left|\sqrt{d_2^{1\mathrm{var}}} - \sqrt{d_2^{2\mathrm{var}}}\right| + \\ &+ \left|d_2^{1\min} - d_2^{2\min}\right| + \left|d_2^{1\max} - d_2^{2\max}\right| \end{aligned} \qquad (3)$$

Note that standard deviation is considered rather than variance. This distance is used to compare the absolute values of the color of the spot. That means the "general" color aspect of the defect.

The third proposed distance is based on the average size of the spots in the image. It is the absolute difference of the size descriptors of the two images:

$$D_3\left(d_3^1, d_3^2\right) = \left|d_3^1 - d_3^2\right| . \qquad (4)$$

Many combinations of the three distances has been tested, e.g. a combined distance with different weights. Experiments showed that the best solution is a multi-step classifier. Given a new image, it is compared with all the images in the dataset using only one of the proposed distances. The N most similar images in the dataset, according to this distance, are selected. Matching is then made using one of the other two distances within this image subset, and the M ($M<N$) best images are extracted. A final comparison is made, within this new subset, using the last metric, and the best image is shown. If this image is affected by foxing, the new image is classified as foxed.

7. EXPERIMENTAL RESULTS

Tests have been made on an image dataset composed by about 220 images from the Alinari Photographic Archives in Florence. Images in the dataset are affected by several typical defects of old photos (scratches, spots, cracks, foxing, etc.) and has been manually classified by a restoration expert of the Archives. For our experiments, the whole dataset has been used for testing. Each image has been used as a test image and it has been matched to the other images in the dataset. About the 30% of the image is affected by foxing. In table 1 we show our experimental results, for each distance discussed in section 5 and for the 3- step classifier. Tests suggested the best configuration as follows: step 1, histogram distance and N=8; step 2, statistical distance and M=4; step 3, size distance.

Results are compared to those obtained with distances based on three standard color descriptors[4][5]: Color Coherence Vector (CCV), Dominant Color (DC) and Color Structure (CS).

For each distance we show the percentage of correct classifications, of false positives (images without foxing, classified as foxed) and of false negatives (images with foxing, classified as not foxed). Average execution time is also shown to compare the efficiency of the classification methods. For our distances, time is shown for the all-at-once feature extraction and for each matching process. We observed that:

- the statistical descriptor, among our proposed, gives best results, which are comparable to those obtained with standard CCV and DC, but it takes much less execution time;
- the size descriptor gives, as we expect, no good results, because it is not color-based; its role is to refine the retrieve in the last step of the classifier;
- CCV and DC give very similar results;
- CS descriptor gives worst results and is less efficient than the two other standard ones;

The multi-step classifier improves results obtained with the statistical descriptor, with no significant increment in the execution time. Results are slightly better than those obtained by standard descriptors, with much less execution time. Further combinations with the standard descriptors may improve the results.

A multi-step classifier has been implemented using the standard descriptors, with no significant improvements in the results, with respect of the single-descriptor classifiers.

8. CONCLUSIONS AND FUTURE WORKS

Digital analysis is the first step in the preservation process of degraded documents.

The purpose of this paper was not to propose a new detection method, i.e. to find which pixels are affected by a specific damage. We aimed to understand if an image is affected by a damage, giving an interpretation to the information extracted by an existing detection method. In fact detection algorithms may sometimes extract misleading information, if they are applied to images which are not affected by the damage they are designed for.

In our work we analyzed the content of digitized image affected by foxing. A set of low-level descriptors has been presented, to extract information from damaged images, starting from a state-of-the-art detection algorithm. A CBIR-based classifier gives an interpretation to this information, comparing it with that extracted from a dataset of images, affected by several types of degradation. The goal is to discriminate whether the image is affected by foxing or not.

Experiments showed that the proposed application gives same results compared to those obtained using standard descriptors, while our improves the execution time.

Actually we plan to analyze some other typical defects of which old documents are affected (scratches, cracks, spots, fading) in order to find appropriate descriptors for each type of defect. The goal is to implement a more complex classifier which will be able to discriminate between a wide set of damages.

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