

# Content-Based Image Retrieval as Validation for Defect Detection in Old Photos

Edoardo Ardizzone, Haris Dindo and Giuseppe Mazzola  
*Dipartimento di Ingegneria Informatica - Università degli Studi di Palermo*  
*Palermo, Italy*

## 1. Introduction

The art of photography is more than 150 years old, but it has quickly absorbed 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 drawbacks 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 many different factors. In most cases, damages are originated by an inaccurate handling and/or storage of the original image, by chemical factors, or by decomposition of the support caused by age. While the origin of a damage is an essential information for the analysis of defects on the physical support, different defects may look similar once the document had been digitized. Furthermore, once a photo is digitally acquired, defects become part of the image, and their features change.

We proposed our own defect taxonomy, which is based on digital features (shape, color, texture, etc.) of a defect rather than considering its origin. With respect to defects in our taxonomy, several works rely on the analysis of damages in old documents by the study of their digital copies. Cracks, scratches, global fading are defects which have been studied, and digital detection algorithms have been proposed to analyze them. Defect detection means the ability to locate the position of corrupted pixels. Digital detection techniques are designed to analyze images which are affected by a specific defect. They typically give as output a mask into which pixels are labelled as good or bad. However they may sometimes extract misleading information, if they are applied to images which are not affected by the damage they have been designed for.

Content-based Image Retrieval techniques can be used to validate the output of a detection algorithm. The goal is to understand if an image is affected by a specific damage, giving an interpretation to the information extracted by the corresponding detection method. Manual annotation 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 users in this task.

## 2. Digital Defect Taxonomy

A first interesting attempt to classify defects in old photos was proposed in [De Polo et al., 2003]. Defects were classified on the basis of their physical-chemical origin. We noted that the proposed taxonomy was incomplete. Many defects we observed in our image database could not be easily classified in one of the proposed classes. In [Ardizzone et al., 2006] we extended this taxonomy, starting from one used by expert manual restorers of old photos. New defects were added and a more detailed description was given. However, we observed that it was not suitable for “digital” restoration purposes, since it was as well based on the defect physical-chemical origin. For example, an observer won’t be able to discriminate an abrasion from a tear, if their digital versions have similar aspect (see fig. 1).

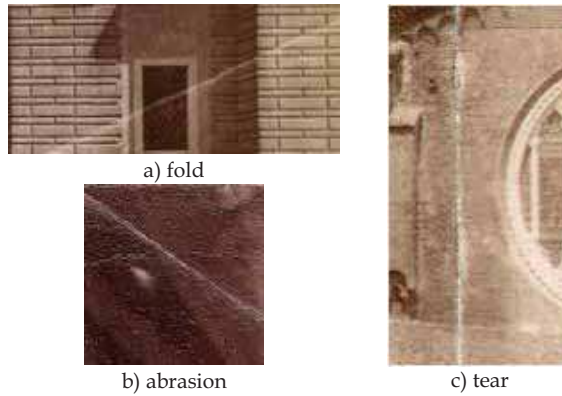


Fig. 1. A comparison between three defects, which have similar digital aspects, but that are caused by different physical factors.

Therefore we proposed a new digital taxonomy [Ardizzone et al., 2009a], which focuses on the digital features of a defect (shape, color, texture, etc.).

DIGITAL DEFECTS	TYPE
Spots	Local
Semi-Transparent Spots	Local
Scratches	Local
Foxing	Local/Diffuse
Folds	Local
Cracks	Local
Deformations	Local
Blotches	Diffuse
Fading	Global
Yellowing	Global
Lacking Color	Local
Lacking Portions	Local
Handwritings	Local

Table 1. The digital defect taxonomy

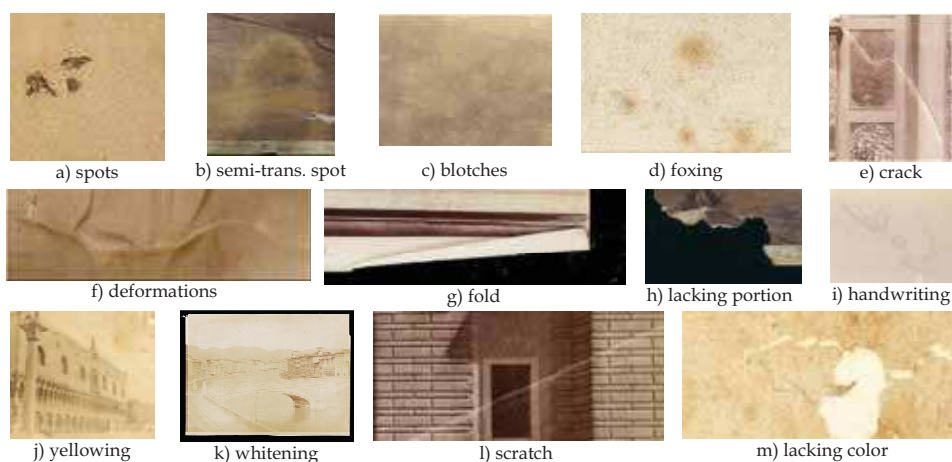


Fig. 2. Some examples of defects classified according to the digital taxonomy (courtesy of Fratelli Alinari Museum Collections (RFMA) in Florence).

Within the proposed digital taxonomy (table 1), a damage can be **global**, if it affects every pixel in the image, **diffuse**, if distributed overall the image, without affecting all the pixels, and **local**, if it is located in a limited portion of the image. According to their digital aspect, defects may be classified as:

- Spots: local defects. Fig. 2.a. Underlying information is lost and must be fully substituted. No specific colors. More or less rounded shaped.
- Semi-Transparent Spots: local defects. Fig. 2.b. Similar to spots, residual information can be recovered with restoration techniques.
- Scratches: local defects. Fig. 2.l. Thin lines, with a preferential direction. Usually lighter than the rest of the image. Can have a darker kernel. Possible limited changing in width and slope.
- Foxing: local/diffuse defects. Fig. 2.d. Covering or semi-transparent spots. It is composed by a dark red- brown kernel, surrounded by a lighter red area, which is usually semi-transparent.
- Folds: local defects. Fig. 2.g. Located near the edges of the photo. It is composed by a lighter central area (the verso side) and darker edges, depending on the acquisition operation.
- Cracks: local defects. Fig. 2.e. Undefined orientation. In some cases they can have branches. Cracks are usually composed by a darker kernel surrounded by a lighter area.
- Deformations (lifting): local defects. Fig. 2.f. Due to the digital acquisition of a non planar support. They look like the negative of a branched crack.
- Blotches: diffuse defects. Fig. 2.c. Semi-transparent spots which can be seen all over the image. Usually lighter than the rest of the image.
- Whitening: global defect. Fig. 2.k. Overall fading.
- Yellowing: global defect. Fig. 2.j. Distortion in the chromaticity (to yellow) of the whole image.

- Lacking color: local defect. Fig. 2.m. Undefined shape (some similar to scratches, some other to spots). Usually white, because of the exposition of the color of the support. Information is totally lost.
- Lacking Portions: local defect. Fig. 2.h. Usually black, but it depends on the acquisition condition. In most cases lacking portions have jaggy edges.
- Handwritings: writings and scrawls. Fig. 2.i. Complex curve lines, darker than the rest of the image.

Note that according our taxonomy a digital defect is no more univocally determined by the cause that generated it. That is, a "digital" spot can be caused by the digital acquisition of defects such as garbage, abrasions or chemical factors. On the other hand, if a printed photo was partially scraped by something, once digitized its digital counterpart may look like a spot, a lacking color, or a scratch.

### 3. Damage Detection in Old Photos

Several works rely on the analysis and restoration of damages in digitized/digital pictures. The problem of detecting, analyzing and removing cracks from digitized paintings has been widely examined in literature [Giakoumis et al., 2006][Abas & Martinez, 2002][Barni et al., 2000]. [Stanco et al., 2005] proposed a method to restore vintage photos affected by water blotches and foxing spots. This method will be further described in section 6.2. [Ramponi & Bruni, 2006] presented a fast technique for enhancing faded images. This method decompose the luminance channel of a faded image in a smooth and in a detail components, using a non linear edge-preserving filter. The two components are then separately processed, to exploit the best available dynamic range, without emphasizing unwanted noise. [Chang et al, 2005] developed a mechanism to automatically detect superimposed defect in a digital photo, including damages by color ink spray and scratch drawing. Their method tried to find inconsistencies in the color properties of a damaged image, working in the HSI space, and proposed an adaptive filter to remove these inconsistencies. In [Ardizzone et al., 2007] we proposed a method to detect and remove quasi-horizontal scratches in digitized aerial photos. We used a pass-band oriented filter, to enhance the horizontal components of the image, the Hough transform, to detect scratch orientation and position, and we proposed a new restoration inpainting technique to remove damaged detected pixels. The detection step was improved in [Ardizzone et al., 2009b], in order to find scratches with any orientation and color, and then a new correlation-based method was proposed to trace the scratch contour. Nevertheless scratches are typical defects of old movie films. In fact many papers dealt with the problem of detecting and removing vertical scratches in vintage movies. [Bruni & Vitulano, 2004] presented a generalized model for scratch detection on digital film materials, on the hypothesis that a scratch is not purely additive to a given image. The proposed detector performs on a hierarchical representation of the degraded image, and successive selections are performed considering both scratch width and height as well as the Weber's law [Joyeux et al., 1999] dealt scratch degradation problem by means of a temporal representation, using all frames of the degraded sequence. In the detection phase the Radon's transform and the combination of the Kalman's filter and the Hough transform are used. Line artifacts are removed using a an interpolation technique, dealing with both low and high frequencies.

#### 4. Validation of Detection Algorithms by CBIR

Content-Based Image Retrieval (CBIR) applications 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. For a complete overview of the existing works in the field of content-based multimedia retrieval see [Lew et al., 2006]. Our idea is to use a CBIR application, in order to compare a damaged image with a dataset of images, affected by several types of degradation. The goal is to understand if an image is affected by a specific damage, using the corresponding detection algorithm.

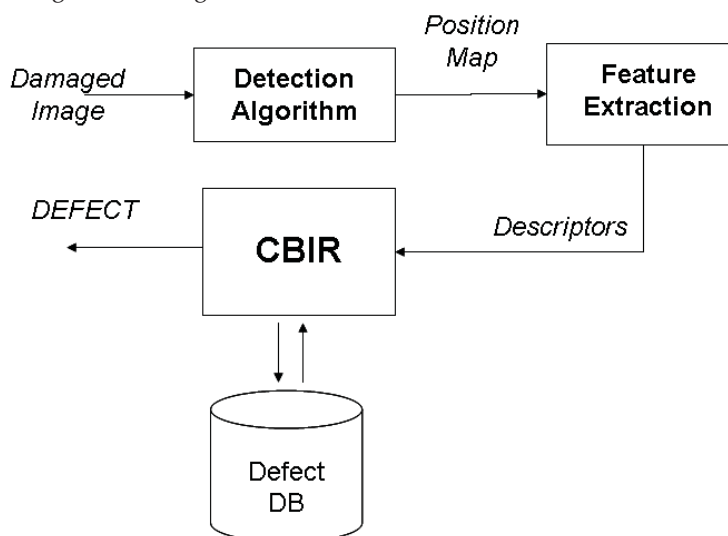


Fig. 3. Scheme of the detection validation process.

In fig.3 the scheme of the detection validation process is shown. A damaged image is processed by a detection algorithm which is designed for a specific defect. Note that the input image could be not affected by that damage. Once we know the position of the damaged pixels, according to the selected detection algorithm, the second step is to extract relevant features from the detected area. That is, we must compute suitable image descriptors, that are the representation of one or more features of an image. The choice of the appropriate descriptors is the critical point of every content-based analysis application. Standard and ad-hoc descriptors can be used in this step. We have observed that pixel statistics (mean, standard deviation, maximum and minimum values, etc) computed on one or more properties (intensity, RGB values, etc.) over the damaged area, can be used as ad hoc descriptors with good results.

Descriptors are then compared, by CBIR, to those extracted from a dataset of images, whose defects have been previously (manually or automatically) annotated. The idea is that, by using suitable metrics to compare the descriptors' values, similar images should have similar values:

- if the most similar image is affected by the selected damage, the detection output is validated, and the area in the image, which had been labelled by the detection algorithm, can be reasonably considered affected by that damage.
- if the most similar image is affected by a defect which is not that corresponding to the detection algorithm, the output is not validated, and the damaged image cannot be classified.

## 5. A case study: detection of foxing spots

A case study for the proposed methodology is presented in [Ardizzone et al., 2008]: Foxing. 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 [Beckwith et al., 1940]. 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 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. 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.

### 5.1 Foxing detection

In this section we briefly present the foxing detection algorithm proposed by [Stanco et al., 2005] 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  $YCbCr$  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. 4 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. 5.a and 5.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. 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.

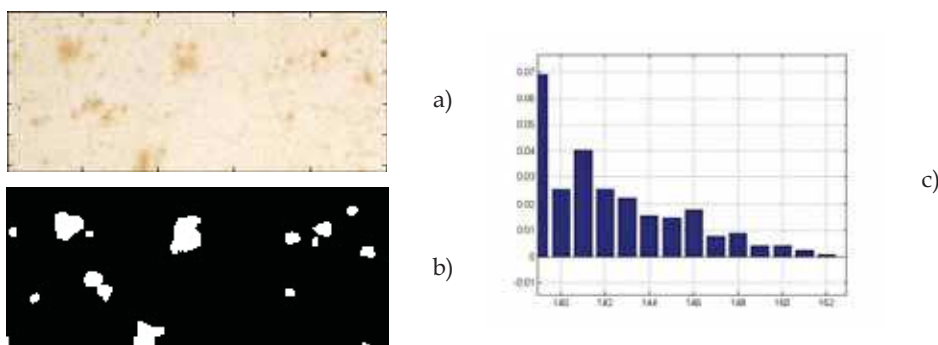


Fig. 4. a) Image affected by foxing spots. b) histogram of the Cr chrominance (zoom on the tail). c) detected damaged area.

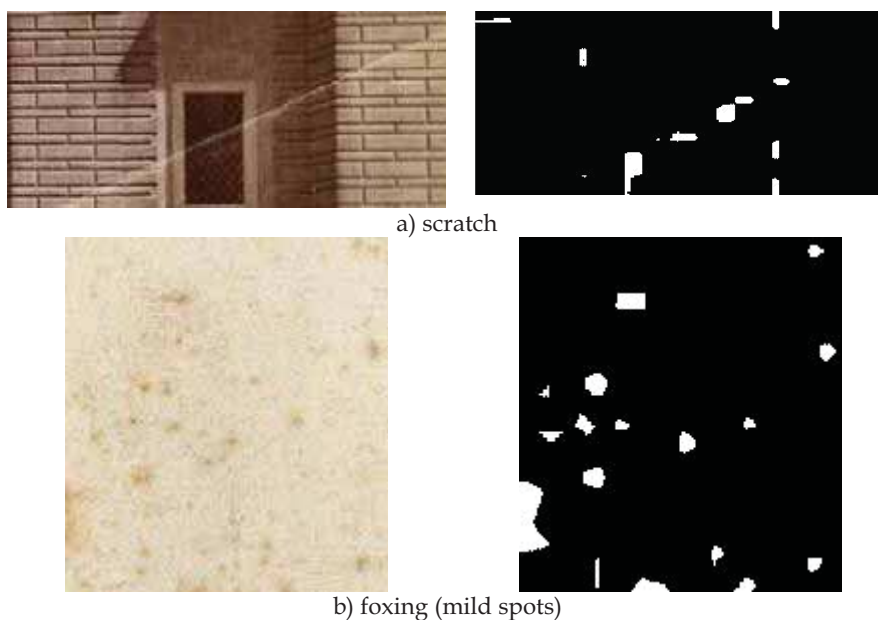


Fig.5. a) Image affected by scratch and the corresponding output mask. b) image slightly damaged by foxing and the corresponding output mask.

### 5.2 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 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 5.1 (see fig. 4.b). Bins and heights of the histogram, from the right to the left of the tail, are stored,

$$d_1 = \{(B_i, h(B_i)) | B_i \geq B_1\} \quad i = 1 \dots 256 \quad (1)$$

where  $B_i$  are the bins of the histogram,  $h(B_i)$ , the corresponding heights and  $B_1$  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  $C_r$  chrominance component: mean, variance, minimum and maximum value. Values are computed only into the damaged area, detected with the algorithm described in section 5.1 (see fig. 4.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. 4.c).

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

### 5.3 Content-based foxing retrieval

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 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  $d_{11}$  and  $d_{12}$ , the descriptors of the two different tails, supposed  $d_{11}$  to have a maximum value  $n$ -units higher than that of  $d_{12}$ , the distance of the two tails is:

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

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:



$$D_2(d_2^1, d_2^2) = |d_2^{1mean} - d_2^{2mean}| + \left| \sqrt{d_2^{1var}} - \sqrt{d_2^{2var}} \right| + |d_2^{1min} - d_2^{2min}| + |d_2^{1max} - d_2^{2max}|. \quad (3)$$

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:

$$D_3(d_3^1, d_3^2) = |d_3^1 - d_3^2|. \quad (4)$$

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.

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			

Table 2. Experimental results

#### 5.4 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 2 we show our experimental results, for each distance discussed in section 5.3 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: Color Coherence Vector (CCV), Dominant Color (DC) and Color Structure (CS).

[Sikora, 2000] [Pass et al., 1996]. 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.

## 6. Conclusions

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

Our purpose is not to propose new detection methods, 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 methods. 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. For this purpose new ad-hoc descriptors are needed for each specific defect.

Our idea is to analyze information extracted by specific detection algorithms, and to use Content-Based-Image-Retrieval applications, to compare it to a set of images which are affected by several defects (our dataset has been previously annotated by hand). Comparing ad-hoc features, we find the most similar image according to these selected features. If it is affected by the defect related to the detection algorithm, the input image can be reasonably considered affected by this defect. That is, information extracted from the input image is similar to that of other images which is affected by that damage. Otherwise input image cannot be considered affected by that damage, because its information is different from what we expected to have.

We presented a study case: images 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 apply our methodology for other typical defects of which old documents are affected (scratches, cracks, spots, fading) in order to find appropriate descriptors for each type of defect.

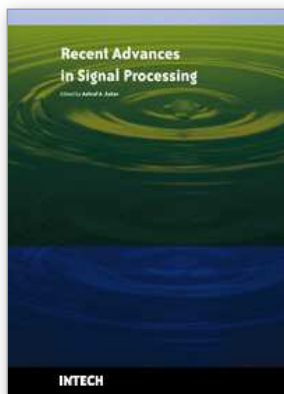
## 7. Acknowledgement

The authors wish to thank the Fratelli Alinari Museum Collections (RFMA) in Florence (<http://www.alinari.com>) for having permitted the use of their photos and their material in this research.

## 8. References

- Abas F. S., and Martinez K. (2002) "Craquelure Analysis for Content-Based Retrieval", In *14th International Conf. on Digital Signal Processing*, July 1-3, 2002, Santorini, Greece
- Ardizzone E., De Polo A., Dindo H., Mazzola G., Nanni C. (2009a) "A Dual Taxonomy for Defects in Digitized Historical Photos", *Proceedings of International Conference on Document Analysis and Recognition*, Barcelona, Spain, July 26-29 2009 (in press)
- Ardizzone E., Dindo H., Mazzola G., Scriminaci M., Vitali M. (2009b) "Multi-Directional Detection of Scratches in Digitized Images" in *Proceedings of European Signal Processing Conference*, Glasgow, Scotland, August 24-28 2009 (in press)
- Ardizzone E., Dindo H., Mazzola G. (2008) "A Set of Low-Level Descriptors for Images Affected by Foxing" in *Proceedings of European Signal Processing Conference*, Lausanne, Switzerland, August 25-29, 2008
- Ardizzone E., Dindo H., Gambino O., Mazzola G. (2007) "Scratches Removal in Digitised Aerial Photos Concerning Sicilian Territory", *14th Int. Conf. on Systems, Signals and Image Processing IWSSIP*, Maribor, Slovenia .27-30 June 2007.
- Ardizzone E., Dindo H., Maniscalco U., Mazzola G. (2006) "Damages of Digitized Historical Images as Objects for Content Based Applications," in *Proc. European Conference on Signal Processing*, 4-8 Sept. 2006, Florence, Italy. EURASIP
- Barni, M., Bartolini, F., and Cappellini, V. 2000. "Image Processing for Virtual Restoration of Artworks". *IEEE MultiMedia* 7, 2 (Apr. 2000), 34-37.
- Beckwith T. D., Swanson W. H., and Iiams T. M. (1940) "Deterioration of Paper: the Cause and Effect of Foxing", *University of California Publications in Biological Science* 1(13):299-356, 1940.
- Bruni V., Vitulano D. (2004) "A Generalized Model for Scratch Detection", *IEEE Transactions on Image Processing*, Vol. 13, No. 1, January 2004.
- Chang, R., Sie, Y., Chou, S., and Shih, T. K. (2005) "Photo Defect Detection for Image inpainting", In *Proceedings of the Seventh IEEE international Symposium on Multimedia*, December 12 - 14, 2005, Irvine, California, USA.
- De Polo A., Stanco F., Ramponi G.(2003), "Towards the Automated Restoration of Old Photographic Prints: A Survey", In *Proc. of IEEE EUROCON 2003*, pp. 370-374, Ljubljana, Slovenia, September, 2003.
- Giakoumis I., Nikolaidis N. and Pitas I. (2006) "Digital image processing techniques for the detection and removal of cracks in digitized paintings" *IEEE Transactions on Image Processing*, vol. 15, no. 1, January, 2006.

- Joyeux L., Buisson O., Besserer B., Boukir S. (1999) "Detection and removal of line scratches in motion picture films", *CVPR'99, International Conference on Computer Vision and Pattern Recognition*, Fort Collins, Colorado, June 1999.
- Lew, M. S., Sebe, N., Djeraba, C., and Jain, R. (2006) "Content-based multimedia information retrieval: State of the art and challenges". *ACM Trans. Multimedia Comput. Commun. Appl.* 2, 1 (Feb. 2006), 1-19.
- Pass G., Zabih R. and Miller J. (1996) "Comparing Images Using Color Coherence Vectors", *ACM Conference on Multimedia*, Boston, Massachusetts, Nov. 1996, pp. 65-74.
- Ramponi G. and Bruni V. (2006) "Virtual Restoration of Faded Photographic Prints", *Proc. EUSIPCO-06, 14th European Signal Processing Conf.*, 4-8 Sept. 2006, Florence, Italy.
- Sikora T. (2001) "The MPEG-7 Visual standard for content description - an overview". *IEEE Trans. on Circuits and Systems for Video Technology, special issue on MPEG-7*, vol.11 pp:696--702, June 2001.
- Stanco F., Tenze L. and Ramponi G. (2005) "Virtual Restoration of Vintage Photographic Prints Affected by Foxing and Water Blotches", *J. of Electronic Imaging*, vol.14, no.4, Oct.-Dec. 2005.



## **Recent Advances in Signal Processing**

Edited by Ashraf A Zaher

ISBN 978-953-307-002-5

Hard cover, 544 pages

**Publisher** InTech

**Published online** 01, November, 2009

**Published in print edition** November, 2009

The signal processing task is a very critical issue in the majority of new technological inventions and challenges in a variety of applications in both science and engineering fields. Classical signal processing techniques have largely worked with mathematical models that are linear, local, stationary, and Gaussian. They have always favored closed-form tractability over real-world accuracy. These constraints were imposed by the lack of powerful computing tools. During the last few decades, signal processing theories, developments, and applications have matured rapidly and now include tools from many areas of mathematics, computer science, physics, and engineering. This book is targeted primarily toward both students and researchers who want to be exposed to a wide variety of signal processing techniques and algorithms. It includes 27 chapters that can be categorized into five different areas depending on the application at hand. These five categories are ordered to address image processing, speech processing, communication systems, time-series analysis, and educational packages respectively. The book has the advantage of providing a collection of applications that are completely independent and self-contained; thus, the interested reader can choose any chapter and skip to another without losing continuity.

### **How to reference**

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Edoardo Ardizzone, Haris Dindo and Giuseppe Mazzola (2009). Content-Based Image Retrieval as Validation for Defect Detection in Old Photos, *Recent Advances in Signal Processing*, Ashraf A Zaher (Ed.), ISBN: 978-953-307-002-5, InTech, Available from: <http://www.intechopen.com/books/recent-advances-in-signal-processing/content-based-image-retrieval-as-validation-for-defect-detection-in-old-photos>

**INTECH**  
open science | open minds

### **InTech Europe**

University Campus STeP Ri  
Slavka Krautzeka 83/A  
51000 Rijeka, Croatia  
Phone: +385 (51) 770 447  
Fax: +385 (51) 686 166  
[www.intechopen.com](http://www.intechopen.com)

### **InTech China**

Unit 405, Office Block, Hotel Equatorial Shanghai  
No.65, Yan An Road (West), Shanghai, 200040, China  
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元  
Phone: +86-21-62489820  
Fax: +86-21-62489821

© 2009 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](#), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.