



*Consiglio Nazionale delle Ricerche
Istituto di Calcolo e Reti ad Alte Prestazioni*

A comparison of algorithms for blue scratch removal in digital images

Lucia Maddalena – Alfredo Petrosino

RT-ICAR-NA-06-11

giugno 2006



Consiglio Nazionale delle Ricerche, Istituto di Calcolo e Reti ad Alte Prestazioni (ICAR)
– Sede di Napoli, Via P. Castellino 111, 80131 Napoli, URL: www.na.icar.cnr.it



*Consiglio Nazionale delle Ricerche
Istituto di Calcolo e Reti ad Alte Prestazioni*

A comparison of algorithms for blue scratch removal in digital images

Lucia Maddalena¹ – Alfredo Petrosino²

Rapporto Tecnico N.:
RT-ICAR-NA-06-11

Data:
giugno 2006

¹ Istituto di Calcolo e Reti ad Alte Prestazioni, ICAR-CNR, Sede di Napoli, Via P. Castellino 111, 80131 Napoli

² University of Naples Perthenope, Department of Applied Science

I rapporti tecnici dell'ICAR-CNR sono pubblicati dall'Istituto di Calcolo e Reti ad Alte Prestazioni del Consiglio Nazionale delle Ricerche. Tali rapporti, approntati sotto l'esclusiva responsabilità scientifica degli autori, descrivono attività di ricerca del personale e dei collaboratori dell'ICAR, in alcuni casi in un formato preliminare prima della pubblicazione definitiva in altra sede.

A comparison of algorithms for blue scratch removal in digital images

LUCIA MADDALENA

NATIONAL RESEARCH COUNCIL, INSTITUTE FOR HIGH-PERFORMANCE
COMPUTING AND NETWORKING (ICAR)
Via P. Castellino, 111 - 80131 Naples, Tel. 081 6139522, fax: 081 6139531
lucia.maddalena@na.icar.cnr.it

ALFREDO PETROSINO

UNIVERSITY OF NAPLES PARTHENOPE, DEPARTMENT OF APPLIED SCIENCE
Via A. De Gasperi, 5 - 80133 Naples, Tel. 081 5476601, Fax: 081 5522293
alfredo.petrosino@uniparthenope.it

1. Introduction

Digital film restoration is an evolving area of image processing aimed at studying methodologies and techniques that allow to digitally restore damaged movies, in order to preserve their historical, artistic and cultural value and to facilitate their diffusion through modern communication media.

Several types of defects can be found in a damaged movie, such as dust and dirt, brightness and positional instability, colour fading, scratches. We are specifically concerned with persistent *scratches*, intended as vertical lines appearing at the same location in subsequent frames of the image sequence. White or black scratches in old movies are mainly due to the abrasion of the film caused by spurious particles present in the camera, during the sequence acquisition phase, or in the projector, during the film projection. Instead, blue scratches, which are the subject of our interest, affect many modern colour movies and are due to spurious particles present in the transport mechanism of the equipment used for the development of the film.

Most of the methods reported in literature that afford this kind of problem are articulated in a *detection* phase and a *removal* phase. Detection consists in searching, among all the vertical lines of the images, those that are not natural lines of the scene, which are characterized as defects; the result of the detection phase over a sequence frame is a binary image, the *scratch mask*, of the same size, where white pixels are related to scratch pixels in the corresponding sequence frame. Removal consists in reconstructing corrupted information only in the defect area individuated by the scratch mask. Being concerned only with the latter phase, in the following we assume that the scratch mask has already been obtained somehow.

Even though the problem of restoration of white or black scratches in digital image sequences has been considered by many authors (see Section 3) and several

commercial software systems include modules for their restoration (such as the *DIAMANT Suite* distributed by HS-ART Digital Service GmbH or the *Revival* distributed by da Vinci Systems, Inc.), the specific case of blue scratches has only recently been addressed [1]. As already mentioned, they generally affect modern colour movies and, therefore, before launching a new motion picture, the film must be digitally restored by companies specialized in digital effects and post-processing. The need for efficient and automatic tools able to digitally remove blue scratches has been the primary input for the reported research.

In this paper we compare several existing methods applied to the removal of blue scratches in digital images, analysing in detail their accuracy on real images.

The contents of this paper are as follows. In Section 2 the features of blue scratches are analysed, in order to understand the basis for removal techniques. Section 3 describes the scratch removal problem and the methods that we consider for the case of blue scratches. In Section 4 we analyse and compare qualitative and quantitative results achieved by the proposed methods on real images. Conclusions are reported in Section 5.

2. Blue scratch characterisation

Blue scratches in a digital image sequence appear as blue strips located along a thin area covering from top to bottom of each sequence frame. An example of blue scratch is given in Fig. 1, which is a detail of a 24 bits RGB colour image, originally of size 2880×2048, belonging to the movie *Animali che attraversano la strada* (2000).

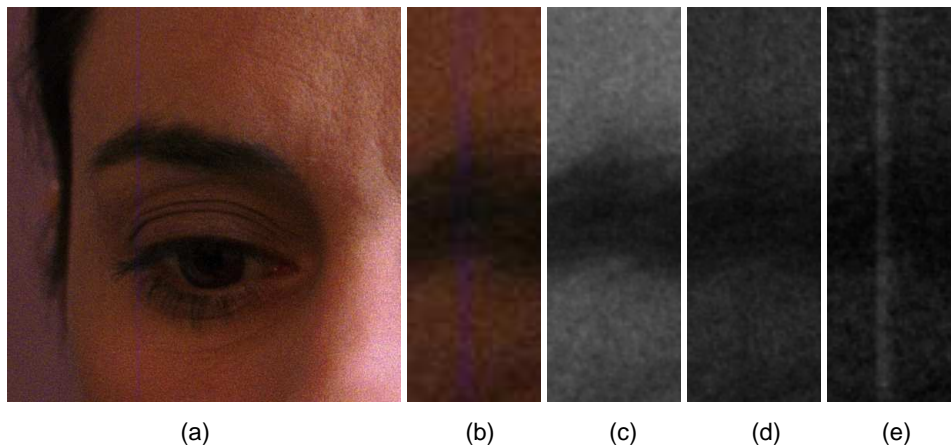


Fig. 1 - Example of a blue scratch: (a) colour image; (b) scratch detail; (c) red, (d) green, and (e) blue band of scratch detail.

Contrary to white or black scratches appearing in dated movies, the direction of blue scratches does not deviate too much from the vertical direction, and their position along the horizontal direction does not change too much (no more than

few pixels) from one frame to the next. Therefore usually blue scratches are not oblique and have fixed position in consecutive frames of the image sequence. This is due to the fact that blue scratches are not caused by improper storage conditions or improper handling of the film, as is usually the case for ancient movies. They are rather caused by spurious particles present in the transport mechanism of the development equipment; in the case of modern equipment, the transport mechanism strictly controls the slippage of the film, which cannot move too much from its rectilinear trajectory. Due to this feature, restoration of blue scratches in image sequences cannot rely on temporal discontinuity of the image intensity function along the sequence; therefore, in the following we concentrate on purely spatial scratch restoration in each image.

Inside the blue scratch area, original information has been substituted by more or less intense blue colour. Specifically, considering the RGB colour space, in the blue band there are increased intensity values compared with the neighbourhood of the scratch; in the green band some of the pixels are altered in an unpredictable way, usually with a slight increase or decrease of intensity values; the red band is usually uncorrupted, although sometimes there could be small fluctuations of intensity values in pixels belonging to the scratch area. These observations are supported by a thorough analysis conducted in [1], where we have analysed all corrupted sequences of the above mentioned movie, identifying the one appearing in Fig. 1 as the most common type.

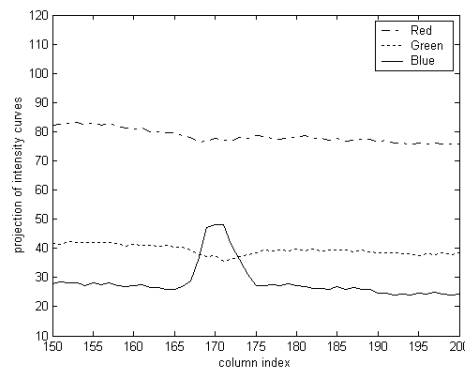


Fig. 2 - Horizontal projection of the image intensity curves of RGB bands of the image of Fig. 1.

In Fig. 2 we show the horizontal projection of the intensity curve (taken as the mean over the image columns of the intensity curve) for the three colour bands of the image of Fig. 1. Here it clearly appears that the horizontal projection of the blue band intensity curve has a ridge in the scratch area. Specifically, in the scratch area the projection of the blue band has a ridge whose width w is about 9 pixels and whose height h is about 25 intensity values; the projection of the green band presents a slight decrease of about 5 intensity values around the centre of the

scratch. The projection of the red band does not show clear effects of the scratch, and red band can be therefore considered as uncorrupted.

Other types of blue scratches include less common cases where the ridge in the projection of the blue band has wider width w (till to 29 pixels) and higher height h (till to 50 intensity values); the green band can present also increasing intensity values around the centre of the scratch, while the red band can be slightly corrupted.

3 Scratch removal

Given a corrupted image and the estimated scratch mask, the scratch removal problem consists in reconstructing corrupted information only in the defect area individuated by the scratch mask.

Depending on the amount of the defect, information included in the scratch area can be either slightly or strongly affected by the defect; thus, the problem can be approached either as a *partially corrupted data* problem or as a *missing data* problem, respectively.

Following the *partially corrupted data* approach, information included in the artefact area is taken into account for the removal. In the case of black or white scratches, some authors adopted such approach and obtained removal through morphological filters [2], interpolation or approximation [3-5], eventually followed by the reconstruction of high-frequency components via Fourier series [3] or via MAP techniques [4].

On the other hand, in the *missing data* approach pixels in the artefact area are considered missing even if they are only slightly altered. This approach has been adopted for black or white scratches by many authors, who obtained removal through interpolation or approximation [6-8], the adoption of autoregressive models [9-10], morphological filters [11], or mean vector filters [12], eventually with the addition of least squares-based grain estimation [7]. Moreover, this approach is the one generally adopted for image *inpainting*, that is the set of techniques for making undetectable modifications to images [13]; such techniques are generally used to fill-in missing data or to substitute information contained in small image regions [14]. Inpainting has been pursued in literature also under different names, such as *image interpolation* [15] and *fill-in* [16-17]; the problem has been afforded also as *disocclusion*, since missing data can be considered as occlusions hiding the image region to be reconstructed [18-19]. Finally, inpainting is also related to *texture synthesis*, where the problem consists in generating, given a sample texture, an unlimited amount of image data which will be perceived by humans as having the same texture [17, 20-22].

Focusing on blue scratches, we have already observed in Section 2 that pixels belonging to the scratch still retain useful information concerning the image structure; therefore the *partially corrupted data* approach seems most amenable. Two methods based on this approach have been considered for the comparative

study of the problem: one [1] has been specifically designed for blue scratches, while the other [23], devised for other kinds of partial colour artefacts, can be applied to the specific case of blue scratches. Moreover, for a more comprehensive comparison, we have also considered two removal methods based on the *missing data* approach: one belongs to the class of interpolating methods [7] and the other one to the class of inpainting algorithms [21]. Both algorithms attempt to reconstruct not only the structure of the image in the scratch domain, but also its texture. All the considered algorithms are briefly outlined in the following.

3.1 Removal algorithms

The Blue Scratch Removal (BSR) algorithm recently proposed in [1] is based on the observation that in uncorrupted areas of the image the displacements of the blue band intensity values from those of the red band are locally roughly constant and the same holds for displacements of the green band from the red band. In the scratch area, instead, such displacements appear strongly varying. Since the red band is usually uncorrupted, the green and blue bands can be restored bringing their displacement from the red band inside the scratch area to the same displacement they have outside the scratch area. The BSR algorithm can be sketched as follows:

Algorithm 1

For each row of the image:

1. Pre-process the red band, in order to take into account cases where the red band appears slightly corrupted;
2. Compute minimum, maximum and median displacement of the green and blue bands from the red band in an uncorrupted neighbourhood of the scratch;
3. Add median displacement to all pixels of the green and blue bands belonging to the scratch area whose displacement from the red band is below minimum or above maximum displacement.

In [23] the authors present a restoration method for films affected by partial colour artefacts resulting mainly from film emulsion melting and the vinegar syndrome. Since the method is based on the observation that the affected areas have not lost their content entirely, but rather the red layer still preserves some of the original image structure, we have adapted the method to the restoration of blue scratches. The removal algorithm proposed in [23] can be sketched as follows:

Algorithm 2

1. Smoothing of the red layer with a Gaussian filter, in order to obtain a reference layer G that retains original information while reducing eventual noise included in the defect area;
2. For each pixel p to be reconstructed:
 - a) Find a “sibling” pixel belonging to an uncorrupted area close to the defect; the search is guided by the image structure still present in the reference

- layer G and gives the pixel q which minimizes a suitable distance from pixel p ;
- b) Paste the RGB values (from the initial unprocessed image) of the sibling pixel q into the current pixel p .

The third scratch removal algorithm taken into account is based on a nonparametric Markovian model adopted in [21] for texture synthesis, and adapted to our purposes. The probabilistic model is based on the assumption of spatial locality: the probability distribution for one pixel given the values of its neighbourhood is independent of the rest of the image. The model is non-parametric in the sense that the probability function is not imposed or constructed explicitly, but it is approximated by a reference sample image, which must be large enough to capture the stationarity of the texture. The algorithm proceeds as follows:

Algorithm 3

For each pixel p to be reconstructed:

1. Determine the sample image C , chosen as a square window centred in p ;
2. Construct the set Q of pixels in C having a neighbourhood *similar* to that of p . The similarity of two neighbourhoods is measured according to the normalized sum of squared differences and it is weighted by a two-dimensional Gaussian, in order to give more importance to the pixels that are near the centre of the window than to those at the edge;
3. Reconstruct pixel p , assigning it the intensity value of a pixel randomly drawn from the set Q .

In order to establish the reconstruction order, for each scratch pixel detected in the binary mask the number of its valid neighbours is enumerated; pixels are then replaced starting from the ones having the most valid neighbours. Scratches are thus simultaneously and progressively filled from the edges to the centre of the scratch. Algorithm 3 has been separately applied to the YCbCr components of the corrupted image.

The last scratch removal algorithm we considered is the one presented in [7], where a simple interpolating method is adopted and the interpolation result is corrected by adding to it the estimated displacement between the adopted model and the real model. Specifically, the procedure consists of:

Algorithm 4

1. Interpolate the pixels pertaining to the scratch domain;
2. Estimate the image texture in the scratch neighbourhood, by computing the displacement between the least square fitting over an uncorrupted neighbourhood of the scratch and the same neighbourhood pixels;
3. Add the estimated texture to the pixels belonging to the scratch domain.

Different versions of the above described method can be obtained by adopting different interpolation methods and neighbourhood shapes. Algorithm 4 has been separately applied to the YCbCr components of the corrupted image.

4. Experimental results

The results of Algorithms 1-4 applied to the corrupted image of Fig. 1 are shown in Fig. 4. Here we can observe that all the algorithms performs in a quite satisfactory way from the subjective visual point of view, even though the inspection of the small printed version of the images does not allow to capture all the details.

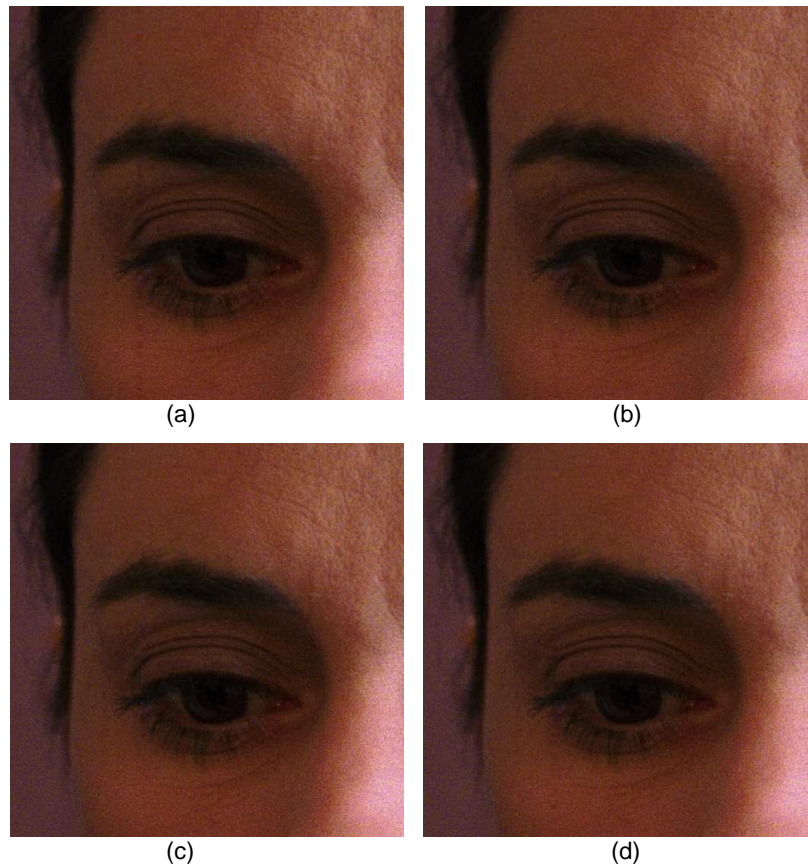


Fig. 4 – Blue scratch removal for the image of Fig. 1 obtained with Alg.: (a) 1; (b) 2; (c) 3; (d) 4.

In order to give a quantitative evaluation of removal algorithms, we have artificially corrupted real images with blue scratches, modelling the horizontal projection of the blue and the green bands in the scratch with a complete cubic spline interpolating extrema of the projection and its maximum point [1].

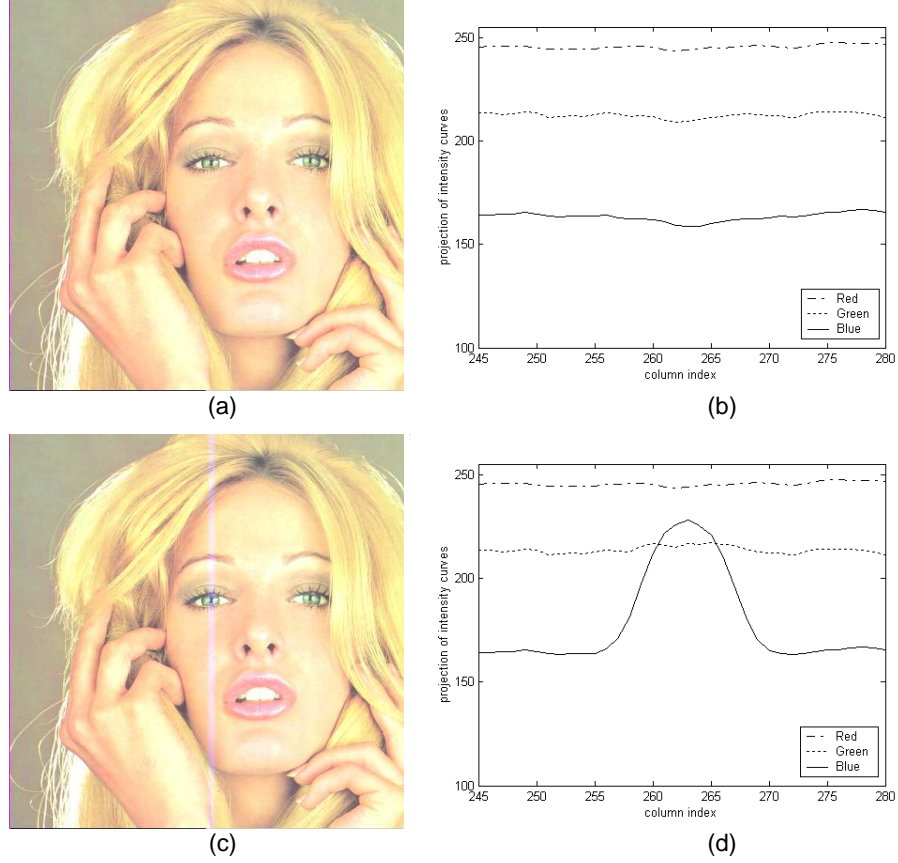


Fig. 3 - Example of artificial blue scratch: (a) original image; (b) horizontal projection of the intensity curves of the three bands of original image; (c) image corrupted with blue scratch of width $w=15$ and height $h=70$; (d) horizontal projection of the intensity curves of the three bands of corrupted image.

Specifically, we considered $L=20$ uncorrupted original RGB images I_l , $l=1, \dots, L$, each of size $N_l \times M_l$; they include well known images (e.g. 'Lena', 'Tiffany') obtained by [24-26], as well as images taken from uncorrupted areas of already digitised images of the movie *Animali che attraversano la strada* (2000). The corresponding images with an artificial blue scratch of odd width w and fixed height $h=70$, denoted as I_l^w , $l=1, \dots, L$; $w=5, 7, \dots, 15$, have been obtained as:

$$\vec{I}_1^w(i, j)^T = \begin{cases} \vec{I}_1(i, j)^T + [0, s_w(j)/f, s_w(j)]^T & \text{if } (i, j) \in \Omega_1^w \\ \vec{I}_1(i, j)^T & \text{otherwise} \end{cases} \quad (1)$$

where $\vec{I}_1(i, j)^T = [I_1(i, j, 1), I_1(i, j, 2), I_1(i, j, 3)]^T$, $\vec{I}_l^w(i, j)^T = [I_l^w(i, j, 1), I_l^w(i, j, 2), I_l^w(i, j, 3)]^T$, Ω_l^w denotes the scratch domain, that is the rectangular subset of the

image domain of size $N_l \times w$ having as first column the centre column $b=M/2$ of the image: $\Omega_l^w = \{(i, j) : i = b, \dots, b + w + 1; j = 1, \dots, N_l\}$, and $s_w(j)$ denotes the complete cubic spline interpolating points $(b-1,0)$, $(b+w/2,h)$, $(b+w,0)$. An example of an image I_l^w artificially corrupted with a blue scratch of width $w=15$ is given in Fig. 3, together with the horizontal projection of the intensity curves for its three bands; all the other artificially corrupted images I_l^w are available at web page [27].

Given the scratch width w , let be, for $l=1, \dots, L$:

- o_l the subimage of original image I_l containing only pixels in Ω_l^w ,
- r_l the subimage of the restored image R_l^w , obtained with BSR algorithm, containing only pixels in Ω_l^w .

The following objective measures for the evaluation of the restoration quality attained by the considered removal algorithms have been adopted:

- *MeanMSE*: mean, over the L images, of the Mean Square Error (MSE) between the original and the restored images:

$$MeanMSE = \frac{1}{L} \sum_{l=1}^L \frac{1}{N_l \times w} \|o_l - r_l\|^2,$$

where $\|\cdot\|$ is intended as vector norm. Such measure gives a nonnegative value; the smaller the value of *MeanMSE*, the better the restoration result;

- *MeanPSNR*: mean, over the L images, of the Peak-Signal-to-Noise-Ratio between the original and the restored images obtained considering the MSE:

$$MeanPSNR = \frac{1}{L} \sum_{l=1}^L \left(10 * \log_{10} \left(255^2 / \frac{1}{N_l \times w} \|o_l - r_l\|^2 \right) \right)$$

Such measure gives a nonnegative value; the higher the value of *MeanPSNR*, the better the restoration result;

- *MeanSSIM*: mean, over the L images, of the Structural Similarity Index [28] applied to the original and the restored images:

$$MeanSSIM = \frac{1}{L} \sum_{l=1}^L \frac{(2 * \mu_{o_l} * \mu_{r_l} + C_1)(2 * \sigma_{o_l r_l} + C_2)}{(\mu_{o_l}^2 + \mu_{r_l}^2 + C_1)(\sigma_{o_l}^2 + \sigma_{r_l}^2 + C_2)},$$

where $C_1=(K_1*A)^2$, $C_2=(K_2*A)^2$, $K_1=0.01$, $K_2=0.03$, and $A=255$. Such measure gives values in $[0,1]$; the higher the value of *MeanSSIM*, the better the restoration result.

- *MeanΔE*: mean, over the L images, of the ΔE average pixel-by-pixel error in CIEL*a*b* between the original and the restored images:

$$Mean\Delta E = \frac{1}{L} \sum_{l=1}^L \frac{\sum_{i=1}^{N_l} \sum_{j=1}^w \Delta E(o_l(i, j), r_l(i, j))}{N_l \times w}.$$

Such measure of the chromatic perceptual difference between the two images gives a nonnegative value; the smaller the value of $Mean\Delta E$, the better the restoration result.

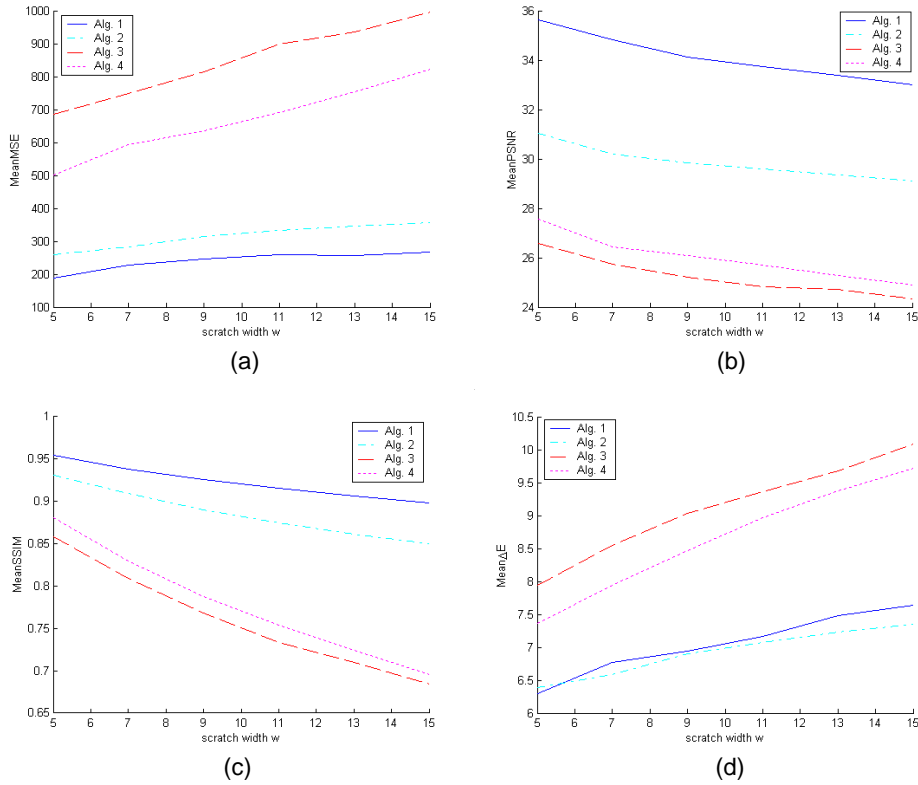


Fig. 5 – Error estimates for blue scratch removal algorithms applied to images described in eqn. (1): (a) $MeanMSE$; (b) $MeanPSNR$; (c) $MeanSSIM$; (d) $Mean\Delta E$.

Results in terms of the described measures obtained by the considered removal algorithms varying the scratch width w are reported in Fig. 5. Here we can observe that both statistical and perceptual properties of the original images are much better restored by the *partially corrupted data* approach (Algs. 1-2) than by the *missing data* approach (Algs. 3-4). Specifically Alg. 1 reaches the best statistical performance and has perceptual performance comparable with that of Alg. 2. Finally, it can be observed that results obtained with all the considered measures show lower accuracy increasing the scratch width w , in accordance with the increasing reconstruction difficulty as the reconstruction area widens.

5. Conclusions

We considered the problem of removing blue scratches from digital image sequences. In particular, we analysed in detail the specific features of such kind of

scratches and compared several removal methods. A thorough analysis of the algorithms accuracy, accompanied by several numerical experiments carried out on both naturally and artificially corrupted images, show that the algorithms based on the partially corrupted data approach produce always much better results than those based on the missing data approach, and allows to individuate the best performance of the algorithm reported in [1].

Acknowledgements

This work has been partially supported by the *Regional Competence Centre for the Development and Transfer of Innovation Applied to Cultural and Environmental Heritage (INNOVA)* funded by Regione Campania, Italy.

Bibliography

1. L. Maddalena and A. Petrosino, "Restoration of blue scratches in digital image sequences", *Image and Vision Computing*, to appear.
2. T. Saito, T. Komatsu, T. Ohuchi, T. Seto, "Image processing for restoration of heavily-corrupted old film sequences", *Proc. of ICPR'00*, IEEE Computer Society, 2000, pp. 17-20.
3. L. Joyeux, S. Boukir, B. Besserer, O. Buisson, "Reconstruction of degraded image sequences. Application to film restoration", *Image and Vision Computing*, vol. 19, 2001, pp. 503-516.
4. L. Joyeux, S. Boukir, B. Besserer, "Tracking and MAP reconstruction of line scratches in degraded motion pictures", *Machine Vision and Applications*, vol. 13, 2002, pp. 119-128.
5. R.D. Morris, W.J. Fitzgerald, A.C. Kokaram, "A sampling based approach to line scratch removal from motion picture frames", *Proc. of ICIP'96*, 1996, pp. 801-804.
6. T. Bretschneider, O. Kao, P.J. Bones, "Removal of Vertical Scratches in Digitised Historical Film Sequences Using Wavelet Decomposition", *Proc. of IVCC'00*, New Zealand, 2000, pp. 38-43.
7. L. Maddalena, "Efficient methods for scratch removal in image sequences", *Proc. of ICIAP'01*, IEEE Computer Society, 2001, pp. 547-552.
8. L. Rosenthaler, A. Wittmann, A. Gunzl, R. Gschwind, "Restoration of old movie films by digital image processing", *Proc. of IMAGÈCOM 96*, France, 1996, pp. 20-22.
9. A.C. Kokaram, R. Morris, W. Fitzgerald, P. Rayner, "Interpolation of missing data in image sequences", *IEEE Transactions on Image Processing*, vol. 4, 1995, pp. 1509-1519.
10. A.C. Kokaram, "Motion Picture Restoration: Digital Algorithms for Artefacts Suppression in Archived Film and Video", *Springer-Verlag*, 1998.
11. E. Decenciere Ferrandiere, "Restauration automatique de films anciens", *PhD Thesis*, Ecole Nationale Supérieure des Mines de Paris, 1997.

12. O. Kao, J. Engehausen, "Scratch removal in digitised film sequences", *Proc. of CISST'00*, CSREA Press, 2000, pp. 171-179.
13. G. Sapiro, "Image inpainting", *SIAM News*, vol. 35, 2002.
14. J. Verdera, V. Caselles, M. Bertalmio, G. Sapiro, "Inpainting surface holes", *Proc. of ICIP'03*, 2003, pp. 14-17.
15. J. Shen, "Inpainting and the fundamental problem of image processing", *SIAM News*, vol. 36, 2003.
16. C. Ballester, M. Bertalmio, V. Caselles, G. Sapiro, J. Verdera, "Filling-in by joint interpolation of vector fields and grey levels", *IEEE Transactions on Image Processing*, vol. 10, 2001, pp. 1200-1211.
17. A.C. Kokaram, "A statistical framework for picture reconstruction using AR models", *Proc. of ECCV Workshop on Statistical Methods for Time Varying Image Sequences*, 2002, pp. 73-78.
18. C. Ballester, V. Caselles, J. Verdera, "Disocclusion by joint interpolation of vector fields and grey levels", *SIAM Journal Multiscale Modelling and Simulation*, vol. 2, 2003, pp. 80-123.
19. S. Masnou, J.-M. Morel, "Level-lines based disocclusion", *Proc. of ICIP'98*, vol. 3, 1998, pp. 259-263.
20. A.A. Efros, W.T. Freeman, "Image quilting for texture synthesis and transfer", *Proc. of 28th Annual Conference on Computer Graphics and Interactive Techniques*, 2001, pp. 341-346.
21. R. Bornard, E. Lecan, L. Laborelli, J.-H. Chenot, "Missing data correction in still images and image sequences", *Proc. of ACM Multimedia*, 2002, pp. 355-361.
22. A.C. Kokaram, "Parametric texture synthesis for filling holes in pictures", *Proc. of ICIP'02*, 2002, pp. 325-328.
23. A. Rares, M.J.T. Reinders, and J. Biemond, "Restoration of films affected by partial color artefacts", *Proc. of EUSIPCO'02*, 2002.
24. Color Texture Analysis, Institut fur Computervisualistik, Universitat Koblenz-Landau, <http://www.uni-koblenz.de/FB4/Institutes/ICV/AGPriese/Research>.
25. Computer Vision Laboratory, Computer Science Department, Univ. of Massachussets, <http://vis-www.cs.umass.edu/vislib/Houses/IM4/images.html>.
26. USC-SIPI Image Database, Electrical Engineering Department, Signal and Image Processing Institute, University of Southern California, <http://sipi.usc.edu/database>.
27. DFR Laboratory, ICAR-CNR, Naples, www.na.icar.cnr.it/~maddalena.l/DFRLab/GC06BlueScratches.html.
28. Z. Wang, L. Lu, A.C. Bovik, "Video quality assessment based on structural distortion measurement", *Signal Processing: Image Communication*, vol. 19, 2004, pp. 121-132.