A model-based method for line scratches detection and removal in degraded motion picture sequences

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Abstract

Line scratches are one of the major defects in degraded archived motion pictures. They appear in the image as lines of bright or dark intensity, oriented vertically and that traverse a considerable portion of the frame. This paper proposes a model-based method for line scratches detection and removal. The image restoration is considered as a two-step process: detection and interpolation of missing data. The line detection is based on a statistical analysis of the gradient orientations in a neighbourhood of the pixel considered as a possible point of the line scratch. If the distribution of the orientations at the prospective point follows the proposed model for line scratches then it is classified as a point of the scratch. The interpolation of missing data is done by proposing a simple model for the degradation effect of the film obtained from experimental considerations on the shape of the gray level profile observed in the degraded zone and estimating the values of the parameters that most likely fit the observed data.

To give some indication of the performance of the detection, artificially corrupted and naturally degraded image sequences were considered and a study of the detection performance is discussed. The proposed algorithm is not computationally expensive. The algorithm for detection has been found to be robust to intensity and shape of the degradations. The assumption that the observed data in the degraded zone have a relation with the original uncorrupted scene information makes the method for interpolation be novel.

Key Words: image restoration, 2-D feature detection, circular statistics

1 Introduction

Line scratches are, joint to blotches, the major defects in degraded archived motion pictures. They appear in the image as lines of bright or dark intensity, oriented more or less vertically and that traverse a considerable portion of the frame. They are classified as stationary defects since they persist approximately in the same spatial location as natural features in the image for more than one frame. Hence, they cannot be characterised as a temporal discontinuity. This fact introduces a level of complexity that makes the problem of line scratches detection be more complicated than the blotch problem detection. These line artefacts are caused when some particle is smeared over the film material in the projector mechanism. These defects occur regularly with archived film material and are specially annoying for the spectator, since they may appear for several seconds on the screen. Coupled with this is the fact that removing unwanted artefacts from video improves the possible compression ratio. The combination of these factors has increased the need for automatic restoring archived material.

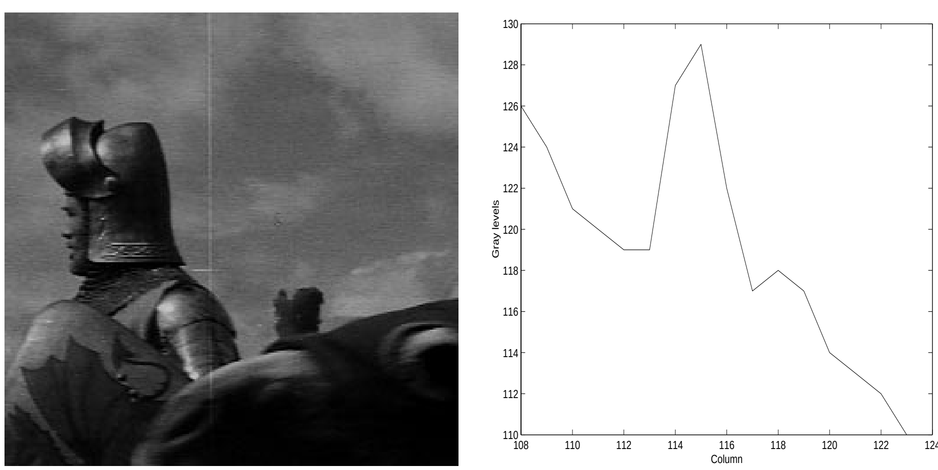
References in the literature about line scratches detection and restoration are limited and quite recent. Two different ways of addressing the problem can be found: a statistical approach and a morphological approach. Both approaches describe the image restoration as a two-step process. The first one involves the detection of the image defects and the second one the interpolation of missing data. The statistical approach was proposed by Kokaram (1996) [1] [2]. He presents a process for generating line candidates based on the Hough transform of the low pass filtered image. These lines candidates are then evaluated by using a model for degradation and adopting a Bayesian framework to choose those most likely to fit the proposed line profile model. Line restoration is later achieved through a stochastic non stationary 2D Auto-Regressive interpolator as a missing data problem. Although good results are obtained, this approach presents some drawbacks. On the one hand, the high computational cost and on the other hand, when large areas of the image are missing there is a subsequent increase in non-stationarity over these regions and insufficient uncorrupted spatial information to operate a restoration. In these cases the 2D Auto-Regressive methods become less useful. The morphological approach was introduced by Decencière (1997) [3]. He characterises a line scratch as a parallelipiped which sides are parallel to the 3D axis and not larger than some fixed levels. The detection and removal of these image artefacts are done by applying morphological techniques, in particular, the top-hat operator is used for line detection and a morphological opening to interpolate missing data. The proposed method is simple and has a low computational cost, but results of the interpolation are somewhat blurred. This effect can be easily noticed in a sequence of images, the rather flat interpolant stands out against the grainy film texture. On the other hand, due to the inherent assumptions of the method, it is not rotationally invariant and can be only applied to detect vertical lines. It is important to note that both approaches assumed that the line scratch has completely obliterated data in the region of the artefact, and hence the observed data bear no relation to the original scene information.

This paper proposes a model-based method for line scratches detection and removal. As in the previous approaches the image restoration is considered here as a two-step process. The line detection is based on a statistical analysis of the gradient orientations in a neighbourhood of the pixel considered as a possible point of the line scratch. If the distribution of the orientations at the prospective point follows the proposed model for line scratches then it is classified as a point of the scratch, otherwise it is ignored. The interpolation of missing data is done by proposing a simple model for the degradation effect of the film obtained from experimental considerations on the shape of the gray level profile observed in the degraded zone and estimating the values of the parameters that most likely fit the observed data. To give some indication of the performance of the detection, artificial corrupted images were considered and a study of the error in the estimation of the location is discussed. The method was also applied on naturally degraded image sequences. The proposed algorithm is not computationally expensive. OJO Comentar los resultados de la detecion e interpolacion.

The paper is organized as follows. Section 2 begins with some observations of the features of a line scratch that can be used to characterise them as a defect in the image and continues with the line scratch model description. Sections 3 and 4 outline the methods for line scratches detection and missing data interpolation, respectively. Finally, experimental results obtained from processing degraded images are presented and discussed in section 5.

2 The Line Scratch Model

It is difficult to propose a general mathematical model for the effect of the abrasion of the film causing the scratches, due to the high number of variables that are involved in the process. However, it is possible to make some physical and geometrical considerations regarding the brightness, thickness and vertical extend of the line. Line scratches can be characterised as follows: (i) they present a considerable higher or lower luminance than their neighbourhood; (ii) they tend to extend over most of the vertical length of the image frame and are not curved and (iii) they are quite narrow, with widths no larger than 10 pixels for video images with a resolution of 576×704. These features can be used to define a useful method for detection. Figure 1(a) shows an image that presents a line scratch. Figure 1(b) shows the gray level profile of an horizontal section of the image at the center of the line. The effect of the abrasion is a considerable increment of intensity levels in the degraded zone, usually accompanied by sidelobes of appreciable amplitude.



(a) (b)

Figure 1: (a) Line scratch at column 115 in an image of 256×256 pixels, (b) Grey level profile of a horizontal section.

Having characterised the line scratch, the following task is to propose a model that takes into account the previous considerations. Since line scratches are zones of the image with clearly defined edges, the gradient image can provide useful information concerning the position and extend of the line.

Let $f(p)$ be the gray level observed at pixel p. From the original image, the smoothed gradient image $\nabla_G f(p)$ is calculated using the Canny operator [4]. It is estimated by convolution with directional filters ∇_x and ∇_y oriented along each grid axis, followed by a convolution with a Gaussian kernel. A morphological closing with a lineal structuring element is previously applied to reduce noise. From now on, we are concerned with a thresholded gradient image defined as follows:

$$g(p) = \begin{cases} \nabla_g f(p) & \text{if } |\nabla_g f(p)| \geq E, \\ 0 & \text{otherwise}, \end{cases} \tag{1}$$

where E is a given threshold. S_g will denote the support of g, i.e. the set of points p where g is not null. The orientation of the gradient is estimated for each $p \in S_g$ as $arctan(\nabla_{Gy}/\nabla_{Gx})$. For every pixel p, let a neighbourhood $N_M(p) = \{q \in S_g : ||p - q|| \leq M\}$, where $||.||$ stands for the Euclidean distance.

Díaz (1997)[5] defined an edge point $p \in S_g$ as a point of the image whose gradient is not null and the observed orientations in $N_M(p)$ are compacted around a preferred direction μ. Noise from the image and the estimation process cause the observed angles to vary around this unknown μ. It was shown that the orientations θ of the gradient follow a von Mises distribution with density

$$h(\theta; \mu, \kappa) = \frac{1}{2\pi I_0(\kappa)} \exp\left(\kappa \cos(\theta - \mu)\right), \tag{2}$$

where μ is the mean orientation and κ is a parameter of concentration around μ. $I_0(\kappa)$ denotes the modified Bessel function of the first type of an imaginary argument and is a normalization factor. The reason to use this distribution is that it allows a direct estimation of the parameters of interest, i.e. the edge orientation μ. In other distributions the geometric interpretation may not be so obvious.

Under the same framework and taking into account the above mentioned geometrical features for line scratches, a *line scratch* can be modelled in image g as the loci of points whose gradient is not null and the observed orientations in a neighbourhood of the point are grouped around two different directions 180 grads apart and orthogonal to the line orientation. In terms of the distribution of orientations, a line scratch of slope μ can be defined as

$$L_\mu = \{p \in S_g : h(\theta) \ in \ N_M(p) \text{ is a mixture of two von Mises distributions}\}, \tag{3}$$

that is

$$h(\theta; \mu_1, \kappa_1, \mu_2, \kappa_2) = \sum_{i=1}^{2} \frac{\lambda_i}{2\pi I_0(\kappa_i)} \exp\left(\kappa_i \cos(\theta - \mu_i)\right), \tag{4}$$

where μ_i represents the vector mean for each edge, κ_i is the measure of concentration about μ_i and λ_i represents the mixing parameter. The two means are assumed to be 180 grads apart,

$\mu_2 = \mu_1 + \pi$, and orthogonal to the line orientation, $\mu = \mu_1 + \pi/2$. Due to the same nature of the data, the two concentration parameters are also assumed to be equal, $\kappa = \kappa_1 = \kappa_2$. From geometrical considerations, it is convenient to choose a rectangular neighbourhood of size $w \times h$ centered at the point, $N_{w\times h}(p)$. In practice, the value $\frac{w}{2}$ has to be lightly larger that the width of the line to be detected. In this way, it arises that $\lambda_i = 1/2 \; \forall i = 1, 2$, since the prospective point is the center of a rectangular window and the two edges have the same length within that window.

From all the above, the relevant distribution for modelling the observed angles is a mixture of two von Mises distributions with density

$$h(\theta; \mu, \kappa) = \frac{1}{4\pi I_0(\kappa)} \{\exp(\kappa \cos(\theta - \mu_1)) + \exp(-\kappa \cos(\theta - \mu_1))\}. \tag{5}$$

This distribution has attracted much attention in the statistical literature. The maximun likelihood equations for estimating the parameters (μ_1, κ) can be obtained, but these cannot be solved analytically. Mardia (1972, page 129) [6] uses the first two sine and cosine moments to obtain these estimates. Regions which have a distribution of the gradient orientations consistent with this model for scratches are classified as such. In Figure 2(a), it is given a linear plot of the distribution of orientations observed at a point of the line scratch shown in Figure 1(a). Note the ciclic nature of the data. The estimated value for μ_1 was 179.14, $\mu_2 = 359.14$ degrees and for κ was 62. Figure 2(b) shows the density function of the mixture in Equation 5 for these particular values of μ_1 and κ.

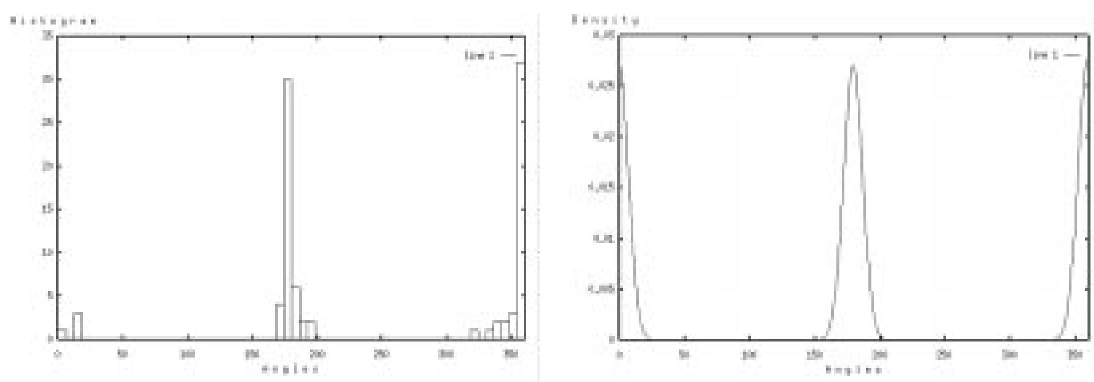


Figure 2: (a) Histogram of orientations observed at a point of the line scratch. (b) The density function of the mixture values for $\mu_1 = 179.14$, $\mu_2 = 359.14$ degrees and $\kappa = 62$.

3 The Line Scratch Detection

From the considerations of the previous section, a natural method for line scratches detection is to study the distribution of the gradient orientations in a neighbourhood of the pixel considered as a possible point of the line scratch. The proposed algorithm works testing the hypothesis "the gradient orientations follow a mixture of two von Mises distributions with density Equation 5" and parameters (μ, κ) estimated from the data. When the hypothesis cannot be rejected at a significance level α_0, this point is then marked as a part of a line and the algorithm goes to analyse the next prospective point, if this occurs. A binary image is generated with the marked pixels. In order to eliminate possible points where the hypothesis cannot be rejected, but that form part of other spurious small vertical structures in the image, a Hough Transform is applied. A threshold H_t is used to obtain the number and positions of the peaks in the *(slope, intercept)* parameter space. Finally, for each peak in the Hough space, the mapping to the space of image points is computed to obtain the set of pixels that lie on each line scratch.

The detection algorithm is explicitly stated below

Step 0 (Initialisation) Fix a gradient threshold level E, a significance level for the test α_0, a size for the neighbourhood $N_{w\times h}(p)$ and a threshold H_t for peak detection in the Hough space. Compute the image g (Equation 1) and estimate the orientation of the gradient at every point $p \in S_g$.

Apply steps 1 to 3 to each pixel $p \in S_g$ in the image.

Step 1. Estimate μ_1 and κ using maximun likelihood equations.

Step 2. Test the null hypothesis "The distribution of gradient orientations in $N_{w\times h}(p)$ follow a mixture of two von Mises distribution (Equation 5)".

Step 3. If the hypothesis cannot be rejected at significance level α_0 then mark p as a point of a line scratch.

Step 4. Compute the Hough transform of the binary image with marked pixels.

Step 5. Obtain the number of peaks n in the Hough space and positions (m_i, c_i) , $i = 1, \ldots n$.

Step 6. (End) For each peak in the Hough space, compute the mapping to the space of image points to obtain the pixels that lie on the line defined by slope m_i and intercept c_i.

The parameters (μ_1, κ) for the von Mises mixture are estimated by using the expressions given in Mardia (1972), i.e. the maximum likelihood equations. The hypothesis is tested by using the Watson-Stephens test [7]. Note, that the neighbourhood $N_{w\times h}(p)$ has to be large enough so as to contain a sufficient number of points in S_g for the test to be applied. The threshold H_t on the height of the peaks in the Hough space has to be chosen carefully to avoid selecting peaks corresponding to spurious lines. Taking into account the assumption that line scratches vertically traverse a considerable zone of the image, a threshold proportional to the vertical size of the image can be chosen. The result is a binary image where each connected component corresponds to a line scratch. These components are then labelled and their maximun value in the Hough image is calculated for each one. The algorithm provides the number of connected components and positions of peaks in Hough space, that is, the number of line scratches that appear in the image and the slope and intercept (m, c) that define each line.

Figure 3 shows the action of the detector on the frame shown in Figure 1(a). This image presents a line scratch at column 115. Initial values for the size of the window was 5×8, for the significance level was 0.05, for the threshold E was 20, and for the peak detection level H_t was 100. The gradient image and the Hough image were normalized in the $[0, \ldots, 255]$ range. The slope and intercept have been quantized in the Hough space to 64 and 128 values, respectively. Figure 3(a) shows the marked pixels result of applying steps 1 to 3. Most of the false detections are at small vertical objects and they can be eliminated by thresholding the Hough image. Figure 3(b) shows the Hough transform. The final result of the detection process is shown in Figure 3(c).

(a) (b) (c)

Figure 3: (a) Result of applying steps 1 to 3 using a 5×8 rectangular window, $E = 20$ and $H_t = 100$. (b) Hough transform with a peak at slope 0 and intercept 58. (c) Final result.

4 The Line Scratch Removal

Once the position of local degradation has been detected, the next step is to remove the distortion by filling in the missing information. In this section a method for missing data interpolation is proposed based on a model for degradation. This model is obtained from experimental considerations on the shape of the gray level profile observed in the degraded zone and estimating the values of the parameters that most likely fit the observed data. The interpolation method relies on the idea that the information in the degraded zone can be used to effect the restoration, if a model for degradation is known. In contrast with the two approaches found in the literature, that consider that degradation has completely obliterated data in the distorted region, the proposed method assumes that the observed data in the degraded zone are related to the original uncorrupted scene information. This consideration makes the method be novel.

In section 2, it was mentioned that the effect of the abrasion in the film is a considerable increment of the intensity. It was also shown that it is accompanied by sidelobes of appreciable amplitude. Kokaram (1998) [1] [2] proposed that the gray level profile of a line scratch with slope m, intercept c and width w can be modelled as a damped sinusoid:

$$L(x,y) = A\ \xi^{|x-my-c|}\ \cos\left(\frac{3\pi|x-my-c|}{2w}\right), \tag{6}$$

where (x, y) are the horizontal and vertical abscissa, A is the amplitude and determines the maximal intensity of the degradation and ξ is the strength of the decay of the brightness, $0 \leq \xi \leq 1$.

From experimental observations on our degraded images, it was found that the model matches quite well the observed line profile for widths of line scratches $w \leq 6$. However, for wider lines residuals are high. These lines are characterised by a central zone with flat intensity, that cannot be reproduced using the previous model. A high value of the damping parameter could be chosen to match the central zone, but it makes the intensity at the sidelobes be considerable higher than the observed one.

To get around this problem, it is proposed a modified model with an additional factor that helps to relaxing the damping at the center of the line. This model assumes that the grey level profile at the line scratch can be modelled as follows:

$$L(x,y) = A\ \xi^{|x-my-c|}\ \frac{\sin\left(2\pi|x-my-c|/w\right)}{|x-my-c|^{a}}, \tag{7}$$

The parameter a smoothes the peakyness of the degradation and is used as a control parameter of the shape of the degradation. For $a = 1$, Equation 7 is a *sinc* function.

Thus, the model of the observed corrupted image G at position (x, y) is assumed to be

$$G(x,y) = I(x,y) + L(x-c,y) + e(x,y), \tag{8}$$

where $I(x, y)$ is the original image and $e(x, y)$ is the prediction error or model residual at location (x, y). It is assumed that these residuals are uncorrelated and a Gaussian random variable having variance σ_e^2 and zero mean.

The problem is now how to determine the parameters so that the profile of the curve best approximates the observed gray level values. From the detection process, the slope m, the intercept c with the horizontal axis and the width of the line w are known. Remember that (m, c) is the location of the peak in the Hough space and w can be obtained from the gradient magnitude. These parameters are constant for all the horizontal sections of the image. However, parameters (A, ξ, a) have to be estimated for each row separately, since the line scratch profile, i.e intensity and shape, can change substantially as it traverses the image and subtraction of a constant profile can leave residual line traces.

The parameter estimation can be done by minimizing the error between the actual and predicted intensity of the pixels,

$$e(x,y) = G(x,y) - I(x,y) - L(x-c,y).$$

The least squares method can be used to obtain these estimates. As estimate of the $I(x, y)$ a nonlinear operator based on rational filter was used [8].

5 Experimental Results

The image restoration process relies heavily on the performance of the detection to produce a successful result in the interpolation step. Therefore this section mainly concentrates on the effectiveness of the detection method.

A simulation was conducted on artificially corrupted images to test robustness of the detection against shape and intensity of the degradation. The scratch profiles were generated using the model for the line scratch described in the previous section and adding a white Gaussian noise. Values of $\sigma = 2, 4$ were used for noise generation. The widths of the line were $w = 4, 8$ pixels and the intensity of the degradation $A = 20, 40$. The slope and intercept of line were randomly chosen. Since line scratches are oriented more or less vertically, the range of variation for the slope was $[0, \ldots, 15]$ degrees. For the intercept the range was the horizontal size of the image. The performance of the detection method was measured in terms of False Positive and False Negative detections. Any line scratch detected in a non degraded zone is termed as false positive (FP), and failure to detect an existing line is termed as false negative (FN).

In Table 1 the performance of the detection process is given calculated from 10 images of the sequence.

	$w = 4$				$w = 8$			
	$\sigma = 2$		$\sigma = 4$		$\sigma = 2$		$\sigma = 4$	
Amplitude	FP	FN	FP	FN	FP	FN	FP	FN
$A = 20$	1	3	–	–	–	–	0	2
$A = 40$	1	2	–	–	–	–	0	0

Table 1: Detection performance in terms of false positives and false negatives for artifical degraded images.

A second experiment was conducted on three naturally degraded image sequences. Figure 4(a) shows one of the 19 frames of the first sequence. This sequence is specially interesting because it presents other vertical structures than the line scratch. Figure 1(a) shows one of the 64 frames of the second sequence and figure 4(b) one of the 26 frames of the third sequence. Sequence 1, 2, and 3 presented 19, 18 and 16 line scratches, respectively. The results of error performance are shown in Table 2.

Sequence 1		Sequence 2		Sequence 3	
FP	FN	FP	FN	FP	FN
1	2	3	5	0	2

Table 2: Detection performance in terms of false positives and false negatives for naturally degraded images.

(a) (b)

Figure 4: Naturally degraded images.

Figure 4(b) shows the result of applying the detector and interpolator to a naturally degraded frame shown in Figure 4(a). The action of the interpolator can be only judged by visual comparison. The visual quality is clearly much improved. It should be noted that the visibility of the interpolated line is always further reduced after subsequent processing such as noise reduction.

(a) (c)

Figure 5: (a) Restored image. (b) Zoom of the line scratch zone.

6 Conclusions

The algorithm for detection has been found to be robust to intensity and shape of the degradations.

The method for removal is able to handle fine textures.

The proposed method can be used to detect line scratches oriented in any direction.

The assumption that the observed data in the degraded zone have a relation with the original uncorrupted scene information makes the method for interpolation be novel.

To be completed

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