Line Scratch Detection on Digital Images: An Energy Based Model

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ABSTRACT

In this paper, a model for automatic detection of line scratches on digital images is proposed. It consists in a generalization of the Kokaram's model using width and height features of the line profile along with Weber's law, to test scratches visibility on the image. Experimental results show that the algorithm works better than the existing models in detecting true scratches with a lower computing time.

Keywords: Digital Film Restoration, Scratch Detection, Weber's Law

1 INTRODUCTION

Line scratches are common defects of old film sequences, caused by the abrasion of the film material during film transport or the developing process. They consist of long, vertical lines of bright or dark intensity, oriented more or less vertically over much of the image, with width from about 3 to 10 pixels [Kokar96], [Kokar98], [Schal99], [Joyeu99], [Joyeu00].

The detection phase results difficult because lines can represent natural components in the scene and occupy the same or nearly the same location in several subsequent frames. Thus such defects cannot be detected as temporal discontinuities of image brightness. According to this fact, each frame is to be analysed separately by means of an algorithm with a low computing time and almost completely automatic, such as reducing or entirely removing operator's interaction.

However some observations on the typical line-profile can be made, so that thickness, contrast and vertical extend of the line can be used to define its features as a defect.

The only spatial model for detection has been proposed by Kokaram [Kokar96],[Kokar98]. His technique consists in two parts: the first one employs deterministic methods based on the geometric technique of the Hough Transform; the second part uses a Bayesian refinement based strategy which rejects or accepts candidates from the previous stage. Though an interesting formulation describing scratches, it has some drawbacks such as a quite huge computational cost along with a number of thresholds to be tuned by the user. Moreover it detects only lines extending over most of the image without distinguishing image defects (scratches) from image features (*false alarms*).

In the following we will show that the elimination of the hypothesis of additivity, i.e. considering a scratch as a partial lack of the image information, along with some considerations about visibility of the scratch, allows us to considerably improve the

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model performances. In other words, our model consists in a generalization of the Kokaram's one that allows us to obtain an algorithm that

- is completely automatic except for the binary choice of the color defect (black or white)
- is able to detect almost all kinds of scratches (see below to better understand this point)
- has a low computing time (linear on the number of the columns except for the cross-section computation)
- proposes an approach to distinguish image features (*false alarms* as the rope in Sitdown image) from image defects.

As we have mentioned before, both models detect scratches using one frame at a time. In [Joyeu99], [Joyeu00] is presented another model for the detection, based on temporal features of a scratch. Thus, considering the whole corrupted sequence, true scratches are detected by means of a Bayesian estimation technique, the Kalman filter. This method presents the same previously mentioned drawbacks.

The organization of the paper is as follows. Section 2 presents Kokaram's model. In Section 3 we propose our model whose experimental results are presented in Section 4. Some concluding remarks constitute the topic of Section 5.

2 KOKARAM'S MODEL

Let's define the sequence

$$x(n) \in \ell^2(R), \quad n = 1, \ldots, N$$

as the horizontal luminance cross-section of the image and $\Omega = [M \times N] \in \ell^2(R)$, the image domain. $x(n)$ is obtained by taking the vertical mean of columns after correcting for a space varying local mean image intensity [Kokar96], [Kokar98].

Observing $x(n)$'s shape, we can assert that in correspondence of the defect position it presents a peak (maximum for white scratches, minimum for the black ones) and it is similar to a damped sinusoid, i.e.:

$$L_n^{(p)}(i,j) = b_p k_p^{|i-(m_p j + c_p)|} \cos\left(\frac{3\pi|i-(m_p j+c_p)|}{2\omega_p}\right)$$

where (i,j) are respectively the horizontal and vertical abscissa, m_p, c_p are the slope and intercept with the horizontal edge of the image, b_p is the brightness of the central portion of the scratch, k_p is the decay of the line profile and w_p is defined as the line width.

Considering scratch as an information that hides the original image one, Kokaram proposes a purely additive model that can be written as follows:

$$I(\vec{x}) = G(\vec{x}) + \sum_{p=0}^{P-1} L_n^{(p)}(\vec{x}) + e(\vec{x}) \quad (1)$$

where I is the degraded image brightness, G is the original image brightness, $\vec{x} = [i,j]$, P is the number of scratches on the degraded image, $e(\vec{x})$ is an additive gaussian noise $\sim \mathcal{N}(0, \sigma_\epsilon^2)$.

According to the fact that the scratch vertically occupies almost all the image and its line profile has noticeable horizontal impulsive features, the degraded image is firstly subsampled after using a low-pass filter [Schaf81] and then horizontally filtered by a median filter. If I_s is the vertically subsampled image and M_s the horizontal one, the signal $e(i,j) = I_s(i,j) - M_s(i,j)$ is then thresholded to obtain $B(i,j)$ defined as follows:

$$B(i,j) = \begin{cases} 1 & \text{if } e(i,j) > e_t(i,j) \\ 0 & \text{otherwise} \end{cases}$$

where e_t is the threshold. The geometric technique of the Hough Transform [Jain89][Canto94] is then used to identify the lines in $B(i,j)$. This transform maps lines in (i,j) space onto points in (m,c) space (the Hough space), where m, c are the gradient and intercept on the j-axis respectively. Strictly speaking, $A(c,m)$ is the accumulator array which samples the Hough space,

$$\forall\ (i,j)\ :\ B(i,j) = 1,$$

$$A(c,m) = A(c,m) + 1 \quad if \quad i = mj + c$$

$\forall\ (c,m)$ belonging to a suitable range considering that scratches can be slightly curved (up to 5% of the width of the film [Schal99]). Peaks in the accumulator array represent lines in $B(i,j)$. We have to underline that at this stage the operator has to tune thresholds relative to the length of a scratch, (i.e. the height of a selected peak) and to the maximum number N_1 of scratches to be detected. Moreover, to avoid aliasing in the Hough space, a 2-D Gaussian filter has to be employed. Consequently the first N_1 peaks exceeding their height threshold are selected, that is candidate lines in $B(i, j)$ are selected and all pixels set to 1 in $B(i, j)$ and which are within $\omega_t/2$ pixels from the candidate line in $B(i, j)$, are taken off the accumulator array (ω_t is the greatest line width). A Bayesian refinement technique is now performed to detect real scratches. This strategy is based on the examination of the marginal distribution for the scratch brightness, $p(b_p)$. Then the *line feature is assumed to be significant if*

$$p(b_p \leq 1.0) < Rp(b_p > 1.0).$$

$p(b_p)$ is computed performing the Gibbs sampling technique on the parameters vector $P = [k_p, b_p, \omega_p, m_p, c_p, \sigma_\epsilon^2]$ [Kokar96][Kokar98].

3 THE PROPOSED MODEL

Before showing our model it is worth spending some words about some kinds of scratches. We have seen that a scratch is usually described to extend on almost all the frame ([Kokar96], [Kokar98], [Joyeu99], [Joyeu00], [Schal99]). Nonetheless, looking at various degraded images, two kinds of scratches can be identified so that a more detailed classification can be made:

- *Principal scratches*, extending vertically on more than 95% of the image. An example is at column no.222 of Sitdown image (Fig. 1);
- *Secondary scratches*, very short, usually not higher than half image. More precisely they have a length up to 95% of image height. See for instance column no.257 of Sitdown image (Fig. 1).

We have to point out that all scratches (principal or secondary) can present another scratch at a distance of few pixels and having sidelobes influencing each other (Fig. 2). Consequently a scratch can be *alone* (see column no.50 in Fig. 8) or *not alone* (see column no.165 in Fig. 8).

Coming back to Kokaram's algorithm, in the detection phase, it treats the scratch as an information lying on the original image one. As a matter of fact, according to the action of the projector, scratch must be considered as a region of partially missing data. Thus Eq. 1 can be generalized as follows:

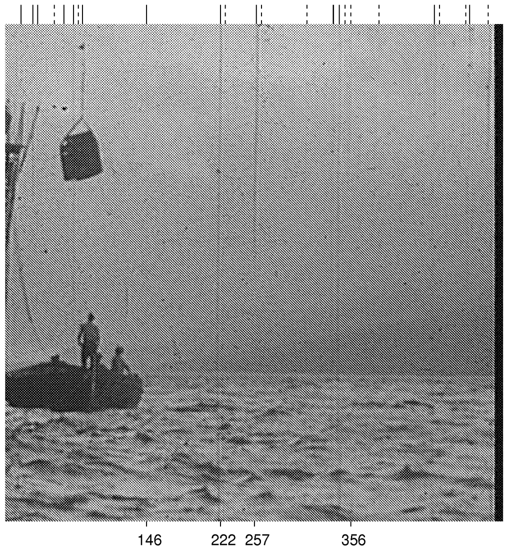

Figure 1: 512 × 512 × 8 bits Sitdown image: Top) detected (solid lines) and not detected (dashed lines) scratches by the proposed algorithm.

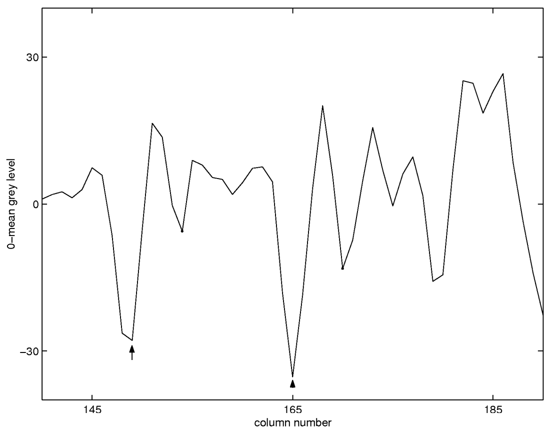

Figure 2: Cross-section profile of two scratches that are *not alone* (see arrows)

$$I(i) = (1 - (1-\gamma)\, k_p^{|i-c_p|}) \quad G'(i) + +(1-\gamma) \quad k_p^{|i-c_p|} \quad L_n^{(p)'}(i). \quad (2)$$

We outline that we use only the horizontal abscissa i because we are focusing on the cross section profile. Moreover

$$G' = G + e$$

because we are interested only in discriminating scratches on the image. Finally $L_n^{(p)'}$ is a simple sinusoid, i.e.:

$$L_n^{(p)'} = b_p \cos(\frac{3\pi|i - c_p|}{2\omega_p}).$$

Eq. 2 is confirmed by the careful observation of the cross-section profile nearby a line scratch. Strictly speaking, observing the line profile along its vertical extension (as shown in Fig. 3), we can note that the intensity of its luminance is considerable, compared to the rest of the signal which is almost smooth. Consequently we can assert that in correspondence of that position we have only information about the line scratch. We express this fact using the coefficient k_p.

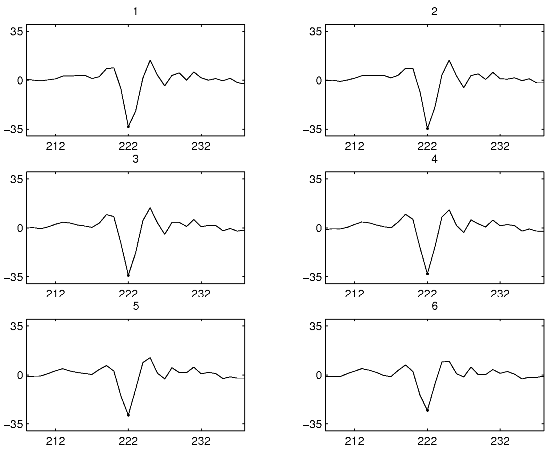

Figure 3: Cross-section profiles of an evident part of the scratch at column no. 222 (top of Sitdown image). 50×30 size regions have been considered along the vertical extension of the scratch.

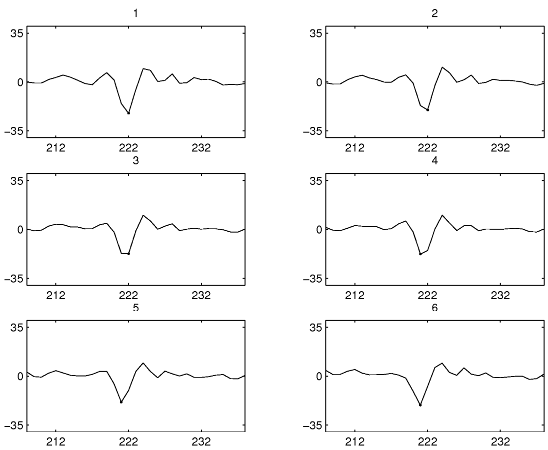

Figure 4: Cross-section profiles, as in Fig. 3, of a bit less noticeable part of the scratch at column no. 222 (bottom of Sitdown image).

If we keep on following line profile (Fig. 4), we note that when it assumes weak intensity values (scratch isn't too much visible on the image), it changes its position and the neighbouring pixels assume similar grey levels. Then we deduce that the signal is strongly influenced by the visibility of the scratch and the model has to include the measure of the ratio between the height of the signal at the scratch peak location and the rest of the signal. For that reason we introduce the coefficient γ defined as follows:

$$\gamma = \frac{E^{+}[x(n)]}{\alpha b_p}$$

where $E^{+}[x(n)]$ is the average of the difference of adjacent extrema of the cross section $x(n)$ (see 1^{st} in Fig. 5), and α is a normalization factor such that γ assumes values in the range [0,1]. In our experimental results we have set α to 10. It is not the only value α can assume. In fact, since it is tied to all the possible ratios between the height of the signal and the scratch one, we have empirically found that all values in the range [6,10] are good.

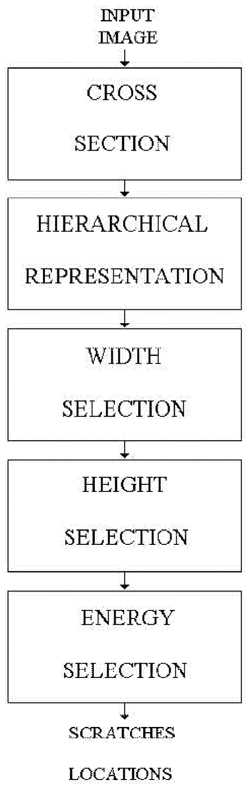

Figure 5: Block scheme of the proposed algorithm

According to the fact that a scratch is represented by a peak on the $x(n)$'s profile, we introduce a hierarchical representation (see 2^{nd} block in Fig. 5) focusing on the sequence $s(k)$ which is composed by $x(n)$'s local extrema.

In order to simplify the description of the algorithm, from now on we will focus only on black scratches, since for the white ones it is symmetric. It turns out that the candidates are the $x(n)$'s minima.