

# Film Line Scratch Removal Using Kalman Filtering and Bayesian Restoration

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## Abstract

*A suitable detection/reconstruction approach is proposed for removing line scratches from degraded motion picture films. The detection procedure consists of two steps. First, a simple 1D-extrema detector provides line scratch candidates. Line artifacts persist across several frames. Therefore, to reject false detections, the detected scratches are tracked over the sequence using a Kalman filter. A new Bayesian restoration technique, dealing with both low and high frequencies around and inside the detected artifacts, is investigated to achieve a nearby invisible restoration of damaged areas.*

## 1 Introduction

Digital film restoration has only very recently been explored [11] [13][16][14][5][2][4] [9]. Up to now, old films have been restored using traditional film restoration techniques, like chemical baths or film polishing. However, such techniques do not permit the removal of all kinds of degradations. Computer-aided techniques have also been used to restore classic old films but they remain very expensive and take several months for the treatment of just one movie. Digital restoration let us expect results beyond today's limitations (automated processing, correction of photographed dust spots and scratches, removing large defects,...) in far less time than traditional or computer-aided techniques. A significant productivity gain should then be achieved for the motion picture industry.

In contrast to classical image sequence restoration, an automatic digital film restoration system is further complicated by severe constraints :

- The old films must be scanned at high resolutions in order to preserve the definition and the visual quality of the motion picture images. Therefore, each frame is scanned at 2K resolution (2200 pixels x 1640 pixels) in a 12 bits/pixel range.
- The restoration algorithms must also preserve the visual quality of the films.
- The processing power has to be cheap, processing time as short as possible and the restoration process should be automated, to cut exploitation costs.

Most existing work on old film restoration is based on the video format [11][13][16][14][5][4]. If we apply these techniques on 2K images, they will involve high computational costs. Besides, motion picture (35mm) images require a much better visual quality than video, thus increasing the complexity of the digital restoration task.

Our digital restoration system handles the automatic removal of the most frequent artifacts damaging old films such as dust spots [2], frame jitter and line scratches [9][8]. In this paper, we will mainly focus on the removal of the latter defects. Our approach involves accurate detection of the line scratches followed by the reconstruction of damaged areas. This is an effective way of decreasing computation and increasing output quality. The same scheme has been adopted by several work related to film restoration [11][13][5][2][10].

## 2 Line scratch detection

Line scratches are easily visible as vertical lines of bright or dark intensity, oriented more or less vertically over much of the image. Detection is complicated by the fact that lines occur as natural part in interesting scenes. Furthermore, the defect persists in nearby or the same location across several frames. Thus, detection of line artifacts cannot rely on temporal discontinuity in image brightness.

Rather than using only one frame to detect line scratches [13][12][5], we focus on temporal features, even for not perfectly vertical line scratches. Indeed, one has to check the behavior of potential line artifacts over the film sequence to reject false detections.

### 2.1 Vertical sub-sampling before detection

A line scratch is a local extremum of the intensity curve along the x-axis. Film grain, dust spots and scanner artifacts introduce noise. We rely on Radon projections along the y-axis to minimize noise influence [15]. This vertical sub-sampling is a simple and efficient procedure to enhance vertical line features and reduce noise [12] [14]. Thus, line artifacts become vertically smooth but remain horizontally impulsive.

Given a gray scale image,  $I$ , our data projections may

be expressed as :

$$\mathcal{P}_H(x, i) = \sum_{j=0}^{H-1} I(x, j + H.i) \quad (1)$$

Projection height  $H$  is estimated in relation with the greatest acceptable angle to the vertical (less than 5 degrees in practice) and the image resolution.



Figure 1: Frame of "Les allumettes suédoises" video sequence (720 × 576)

## 2.2 Detection of line artifacts

Following line scratch features should be extracted from the digital image : location with respect to the x-axis, angle to the vertical, width. Local extrema within each projected strip can be detected using classical techniques such as gray scale morphology [5][2], Median filtering [7][11], 1D-extrema detection and Ridge detection [3]. We have experimented the three former methods and have obtained results of similar quality [8]. We have chosen the detector which requires the tuning of the minimum number of parameters : the 1D-extrema detector which is used without parameter tuning (threshold value  $\lambda$  fixed at 0). Figure 2 shows the result of this detector on a *telecine* sub-sampled film sequence "Les allumettes suédoises" (see figure 1). To extract the width of the line scratch we use a step detector [8].

The thresholds are fixed at low values in order to detect every line artifact. This also increases the number of wrong detections but the tracking process will eliminate them. The detection results show a great number of false detections. Indeed, the detection process is further complicated by the high intensity noise of this film sequence.

## 3 Line scratch tracking

In this section, we aim at tracking the detected line artifacts over the image sequence to refine the previous spatial detection process. An accurate detection field may be



Figure 2: Line scratch detection on "Les allumettes suédoises" sub-sampled sequence (10 frames with 16 pixel-height stripes)

achieved to allow a suitable reconstruction of the deteriorated areas. Indeed, the first detection step only provides an approximate detection field which may contain false detections. A powerful technique for doing such tracking process is the Kalman filter [17][8].

### 3.1 Kalman filter

The Kalman filter is a Bayesian estimation technique used to track stochastic dynamic systems. The filter is based on two probabilistic models :

- The system model which describes the evolution over time of the current state vector  $u_k$ . The transition between states is characterized by the known transition matrix  $\Phi_k$  and the addition of Gaussian noise with a covariance  $Q_k$ .
- The measurement model which relates the measurement vector  $d_k$  to the current state through a measurement matrix  $H_k$  and the addition of Gaussian noise with a covariance  $R_k$ .

$$\begin{aligned} u_k &= \Phi_k u_{k-1} + \eta_k, \quad \eta_k \sim N(0, Q_k) \\ d_k &= H_k u_k + \xi_k, \quad \xi_k \sim N(0, R_k) \end{aligned} \quad (2)$$

The standard Kalman filter relies on linear models. However, the extended Kalman filter allows the use of non linear state and measurement models. The extended Kalman equations are defined as :

$$\begin{aligned} u_k &= f_k(u_{k-1}) + \eta_k, \quad \eta_k \sim N(0, Q_k) \\ d_k &= g_k(u_k) + \xi_k, \quad \xi_k \sim N(0, R_k) \end{aligned} \quad (3)$$

Kalman filter algorithm operates in two phases : prediction and update [8][17]. The prediction equations may be expressed as follows :

$$\begin{aligned} \hat{u}_{k/k-1} &= f_{k-1}(\hat{u}_{k-1/k-1}) \\ \hat{P}_{k/k-1} &= \Phi_{k-1} \hat{P}_{k-1/k-1} \Phi_{k-1}^T + Q_{k-1} \end{aligned} \quad (4)$$

with :

$$\begin{aligned} \Phi_{k-1} &= \left. \frac{\partial f_{k-1}(u_{k-1})}{\partial u_{k-1}} \right|_{u_{k-1} = \hat{u}_{k-1/k-1}} \\ H_{k-1} &= \left. \frac{\partial g_{k-1}(u_{k-1})}{\partial u_{k-1}} \right|_{u_{k-1} = \hat{u}_{k-1/k-1}} \end{aligned}$$

The recursive process is initialized by  $\hat{u}_0$ , an initial estimate of  $u$ , and  $P_0$ , its error covariance matrix.

### 3.2 Spatio-temporal line scratch detection

The first thing to specify when designing the Kalman filter is the representation used for the state vector. In our case, the state vector is related to the position  $x(t)$  of the vertical artifact lines over time.

We have previously developed a line scratch tracking technique based on a cubic polynomial model [9]. However, this method fails in some situations. In particular, the intermittent disappearing of a line scratch over the sequence causes a filter divergence leading to the rejection of the tracked primitive. This filter divergence may also be induced by estimation bias due to the quadratic nature of the underlying cubic polynomial model. We propose here a new scheme based on a non linear model that ensures a more reliable tracking of line artifacts.

Line scratches are usually generated by rubbings against rotating mechanical pieces. Therefore, they should have a sinusoidal evolution over the image sequence. Figure 3 shows that the line scratch position behavior over "Les allumettes suédoises" sequence clearly integrates sinusoidal components. Therefore, we rely on a model with 3 sinusoidal components (1 fundamental and 2 harmonics) :

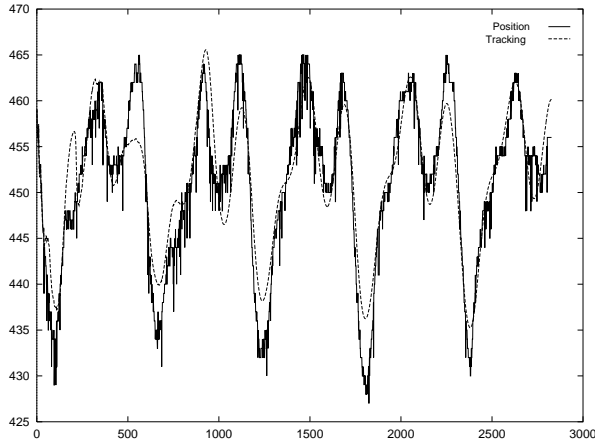


Figure 3: Position of the line scratch and its tracking over 100 frames of "Les allumettes suédoises" sequence

$$x(t) = offset + \sum_{i=1}^3 A_i \sin(2\pi f i t + \varphi_i) \quad (5)$$

where :

- $offset$  is the mean position of the line scratch,
- $A_i$  is the amplitude of the  $i^{th}$  sinusoid,

- $\varphi_i$  is the phase displacement of the  $i^{th}$  sinusoid with respect to the origin,
- $f$  is the signal frequency.

Indeed, a single sinusoid seems to be insufficient to approximate the curve related to the position of a line scratch over time (see figure 3).

Let us notice that the adequate number of harmonics depends on the mechanical nature of the line scratch. However, one has to minimize the number of parameters to estimate through the Kalman filter. The use of 3 harmonics seems to be a good compromise.

The state vector of our line scratch tracking system is :

$$u_k = (A_1 \varphi_1 A_2 \varphi_2 A_3 \varphi_3 f offset)^t \quad (6)$$

The transition and measurement matrices take the following form :

$$\begin{aligned} \Phi_k &= Id \\ H_k &= \left. \frac{\partial d_k(u)}{\partial u} \right|_{u = u_k} \end{aligned} \quad (7)$$

The starting state vector is :

$$u_0 = (0 \ 0 \ 0 \ 0 \ 0 \ 0 \ f_0 \ r_0)^t \quad (8)$$

with :

- $r_0$  the initial position of the detected line scratch,
- $f_0$  the initial value of the signal frequency which has been experimentally fixed to ensure filter convergence.

The covariance matrices are initialized as follows :

$$\begin{aligned} Q_k &= 0 \\ R_k &= 700 \end{aligned} \quad (9)$$

The covariance  $R_k$  has been overvalued to allow a slow evolution of the state vector after convergence. The starting state covariance has also been overvalued to ensure a fast convergence of the Kalman filter.

$$P_0 = \begin{bmatrix} 10^6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 10^6 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 10^6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10^6 \end{bmatrix} \quad (10)$$

The Kalman-based tracking process provides then the trajectories of the potential detected line artifacts. The examination of the obtained trajectories easily permits to distinguish between effective line artifacts and false detections [8]. Let us point out that the tracked lines are extracted from the detection fields using the Hough transform [6]. The search area is limited to a strip centered around the

predicted line artifact. The Hough transform, well-known for its robustness, provides both new measurements for the update tracking stage and the corresponding accumulation value (number of votes in the accumulator array). The latter is used as a confidence value which directly influences the update stage [8]. Only reliable measurements will involve a state vector update. Let us denote  $\gamma$  the normalized confidence value. This coefficient allows the estimation of a new measurement covariance  $R'_k = (1 - \gamma)R_k$ .

The result of our tracking process on the previous "Les allumettes suédoises" sequence is depicted on figure 4. We can notice that the line scratch is well tracked and the number of false detections is low despite the high density of the noisy detection field (see figure 2). These false alarms are easily discarded using a temporal duration threshold. Figure 3 shows that the estimated position curve satisfactorily fits the actual position curve of the line scratch over the whole sequence. Our technique has been validated on two other film sequences [8].

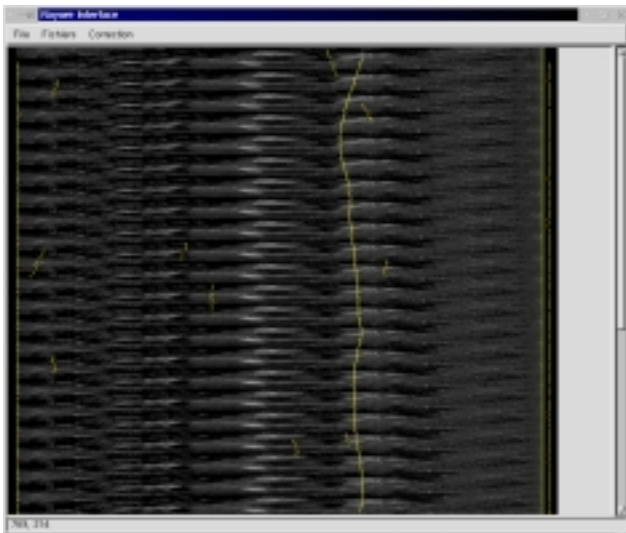


Figure 4: Line scratch tracking over "Les allumettes suédoises" sequence

## 4 Line scratch removal

This stage consists in post-processing the detection field. Due to the very strong structure and effect of line scratches on the appearance of the frame, a high quality restoration is necessary to completely remove these artifacts.

### 4.1 Existing techniques

Numerous image restoration techniques exist but most of them do not or just partially deal with the high frequencies of the images. To our knowledge, very little research

work has been devoted to this issue [13][11][10]. Furthermore, the special case of line scratch removal has only very recently been addressed [13][12][5][9] and remain an unresolved problem. In [5], a morphological technique is used to remove the scratches. However, the resulting restored areas are homogeneous and are therefore easily perceived. This phenomenon would be emphasized in a film sequence. To alleviate this smoothing effect, the author incorporates texture components extracted around the artifact. Morris uses a Markov Random Field (MRF) based interpolation algorithm [13]. However, his results are of insufficient quality. The scratches are not completely removed and remain visible. In previous work, we have developed a Fourier series based restoration technique which seems to produce better results than the Morris technique for the same kind of line scratches [9]. This method first reconstructs low frequency components using a polynomial interpolation and then deals with higher frequencies using Fourier series. However, this technique fails to remove line artifacts such as the one affecting "Les allumettes suédoises" sequence (see figure 5). This is a quite large, poorly contrasted and very noisy (film grain) example of line scratch.

To completely remove the detected artifacts, we propose an efficient Bayesian restoration approach. Unlike the previous techniques, our method takes benefit of the residual information within the line scratch area. Indeed, the abrasion causes the removal of a proportion of the thickness of the emulsion and, in most cases, the density is not completely affected. Morris argued that the effect of a line scratch is to reduce the density by a multiplicative factor [13]. Therefore, he tried to estimate this so-called "depth" factor  $d$ . The underlying idea was to multiply the original gray scale value by  $1/d$ . However, he reported that the resulting restoration was unsatisfactory and therefore not shown. These poor results are mainly due, on the one hand, to the use of the same "depth" factor for the whole line scratch area and, on the other hand, to the increase (or decrease) of noise caused by the factor multiplication operation. Our idea is to replace this problematic multiplicative factor by an additive factor. The equivalence between the two formulations is obvious but, as we will see, the latter seems to be more appropriate for the removal of line scratches.

### 4.2 A Bayesian restoration method

Our restoration technique operates in two stages :

- Reconstruction of the low frequencies of the line scratch area.
- Incorporation of noise (film grain) within the reconstructed area to achieve as seamless a restoration as possible. This concerns the retrieval of the high frequencies of the damaged areas.

### 4.2.1 Polynomial interpolation

The low frequencies of the affected areas are reconstructed using a polynomial interpolation based on a cubic polynomial :

$$P(x) = \sum_{i=0}^n a_i x^i \quad (11)$$

which is the most simple model to approximate low frequency components of an image. The estimation of the model coefficients is based on a least squares technique whose input data are the x-coordinates  $x_i$  of uncorrupted pixels surrounding the line patch. This interpolation provides an estimated profile for each horizontal segment of the previously detected line scratch.

Let us notice that we use somewhat of a spatio-temporal neighborhood because we consider the image sequence as a whole and not as a set of separate frames. Thus, we focus once again on temporal features while the previously related line scratch removal techniques did not at all exploit the temporal dimension of the sequence. Indeed, these methods use spatial neighborhoods around the artifacts to restore the damaged areas [13][5][9].

### 4.2.2 Refinement using a MAP reconstruction

The MAP technique is an iterative estimation process which consists of the following steps :

1.  $k$  noisy observations are considered. The set of observations is denoted :

$$Z^k = \{z(i), i \in [1, k]\} \quad (12)$$

2.  $X$  is the model of the process inducing the data  $z(i)$ ,  $\hat{X}$  the estimation of  $X$  from the data  $z(i)$ . If  $X$  is a random variable with a prior probability  $p(X)$ , the estimation process involves a Bayesian technique.

3. The Bayesian technique consists in estimating the posterior probability of  $X$  using the Bayes theorem [1] :

$$p(X|Z^k) = \frac{p(Z^k|X).p(X)}{p(Z^k)} \quad (13)$$

the prior probability  $p(X)$  being known.

The estimation of  $X$  is achieved using a maximization of the posterior probability (MAP) :

$$\hat{X}^{MAP}(k) = \arg \max_X p(X|Z^k) = \arg \max_X p(Z^k|X).p(X) \quad (14)$$

Both posterior and prior probabilities are usually taken as Gaussian distributions.

In our case, the random variable  $X$  corresponds to the profile  $b(x), \forall x \in [-l/2, l/2]$ , with  $l$  the width of the line scratch, which will permit the reconstruction of the

degraded input mono-dimensional signal (1D-line scratch area). The parameter  $\sigma_{b(x)}$  represents the prior noise of  $b(x)$ . For computational reasons, we choose to use a constant value of  $\sigma_{b(x)}$  for all the pixels lying on the line scratch horizontal segment. This assumption is less severe than the one used by Morris who assumed the same noise for the whole line scratch [13]. Furthermore, the line scratch width is limited to a few pixels ( $\leq 10$  pixels for video resolution).

The data  $Z^k$  are offsets derived from the difference between the estimated profile at iteration  $k$  and the actual values within the line scratch area. The noise  $\sigma_{Z^k}$  related to  $Z^k$  comes from both image noise (grain, scanner artifacts or video noise, etc) and profile estimation errors. For simplicity, we take into account only the former measurement noise component.

We can then derive the probability function related to each pixel within a position  $x$  of the current 1D-line scratch area :

$$p(Z^k(x)|b(x)).p(b(x)) = \mathcal{N}(Z^k(x)-b(x), 0, \sigma_{Z^k}).\mathcal{N}(b(x), \mu_{b(x)}, \sigma_{b(x)}) \quad (15)$$

the aim being the estimation, for each degraded pixel, of the optimum profile (reconstructed image brightness) :

$$b(x)^* = \arg \max_{b(x)} \mathcal{N}(Z^k(x)-b(x), 0, \sigma_{Z^k}).\mathcal{N}(b(x), \mu_{b(x)}, \sigma_{b(x)}) \quad (16)$$

A few developments together with the addition of a common regularization term leads to the following error function [8] :

$$b(x)^* = \arg \min_{b(x)} \left( \frac{(Z^k - b(x))^2}{2\sigma_{Z^k}^2} + \frac{(b(x) - \mu_{b(x)})^2}{2\sigma_{b(x)}^2} + \alpha |b''(x)| \right) \quad (17)$$

where  $\alpha$  represents the regularization coefficient.

Let us notice that a relationship between  $\sigma_{b(x)}$  and  $\sigma_{Z^k}$  may be found from (17) :

$$\sigma_{b^k(x)} = \sqrt{\frac{1-\lambda}{\lambda}} \sigma_{Z^k}, \lambda = \approx^k \sqrt{1 - b^k(x)/Z^k} \quad (18)$$

Fixing the ratio  $b^k(x)/Z^k$  at 9/10 after  $k = 16$  iterations, we obtain  $\sigma_{b^k(x)} \approx \sigma_{Z^k}/10$ .

Our Bayesian restoration technique has been validated on the whole "Les allumettes suédoises" sequence (100 frames). The resulting restored sequence is of high quality, the line scratch having been completely removed as illustrated on figure 5. Our method has also been validated on (2000  $\times$  1500) images [8].

## 5 Summary and conclusion

We have presented an efficient detector of line scratches which are common artifacts in motion picture films. This detector is based on an 1D-extrema localization and a Kalman filter is involved to track the potential scratches

over the frames. Thus, false line scratches are rejected and only the damaged areas are post-processed by our reconstruction method. Our line scratch removal algorithm is an efficient Bayesian technique. The low frequencies of the deteriorated areas are first reconstructed using a simple polynomial interpolation. Then, we deal with the higher frequencies using a MAP reconstruction approach. This restoration method turned out to be a powerful method leading to a nearly invisible restoration. Finally, let us emphasize that our line scratch removal is a fast process : 10 s/video image for the detection step and 2 s/line scratch for the restoration stage.



**Figure 5: Bayesian restoration of an enlarged image part of "Les allumettes suédoises" sequence**

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