IJSTE - International Journal of Science Technology & Engineering | Volume 3 | Issue 10 | April 2017
ISSN (online): 2349-784X

Automatic Restoration of Old films by Removal of Line Scratch and Flicker

Shahnas S M
PG Student
Department of Electronics & Communication Engineering
Marian Engineering College, Trivandrum, India

Monisha Menon
Assistant Professor
Department of Electronics & Communication Engineering
Marian Engineering College, Trivandrum, India

Abstract

Restoration of archived film and video are necessary but challenging. The main challenges faced are noise, texture, change in image brightness and loss of original image information due to decay of film material. This paper proposes two algorithm, spatial filtering algorithm and temporal filtering algorithm for line scratch detection. Spatial filtering algorithm uses a contrario methodology for scratch pixel grouping and validating scratch segment, which makes the algorithm robust to noise and texture. Temporal filtering algorithm rejects false detection due to thin vertical structures by using temporal information contained in the image sequence. The detected scratches are then corrected by inpainting. Finally, flicker correction is done to improve the subjective quality of the video. This concept of eliminating line scratch and flicker can be used to restore old video.
Keywords: A Contrario Methodology, Flicker, Inpainting, Line Scratches, Motion Coherence Criterion, Video Restoration

I. INTRODUCTION

Old film restoration is a subject of great interest to researchers due to large quantities of old film material present in film archives. The aim of old video restoration is to generate an output video which looks better than the source. Old film, including cultural heritage masterpieces are digitally remastered and converted into higher quality formats. Unfortunately, manual restoration is highly time consuming. Therefore, it is necessary to develop some automatic or semi-automatic tool for restoration of old film. In earlier times, the films were recorded in digital tapes. The bad storage condition, manual handling or abrasion affects the film material and causes defects. Some of the common defects in films are dust / dirt, blotches, flicker and line scratches. Here in this work, we consider the defects - line scratches and flicker.

Line scratches are caused by an abrasion to the physical film and in videos they can appear in the form of thin bright or dark lines which are roughly straight and vertical. An important characteristic of line scratch is temporal persistence [1], meaning that they remain in the same spatial position for several frames. The characteristics of line scratches are variable, which makes the detection and restoration a challenging task. In some case scratch is semi-transparent so that some of the original image information is available whereas in some other case it may erase the complete information. Also, the shape of the scratch can vary from frame to frame. Therefore the detection and restoration algorithms need to be adapted particularly to this defect.

Image flickers are the unwanted change in image brightness which do not originate from the scene. It can be caused by several factors such as inconsistent film exposure at the image acquisition stage, ageing of the film, dust, chemical processing, copying and in the case of old film cameras, variations in shutter time. There is a great need for removing these disturbing fluctuations in image brightness to improve the quality of the video.

The contributions of this paper are given below. Firstly we propose a line scratch detection method which comprises of two algorithms: a “spatial” filtering algorithm and “temporal” filtering algorithm. The spatial filtering algorithm detects line scratch in each frame and is robust to noise and texture due to the use of a contrario methodology [10]. Temporal filtering algorithm avoids false detection rather than validating true scratches [11]-[15]. Secondly, the detected scratches in each frame are removed using exemplar-based inpainting. Finally, disturbing fluctuations in image intensities are removed from each frame to increase the subjective quality of the film sequences.

II. METHODOLOGY

In our proposed system, we have accepted a corrupted old video. Initially, the input video is divided into frames and each frame is pre-processed to reduce noise. Spatial filtering algorithm identifies the scratches in each frame .This algorithm uses a contrario methodology, which identifies shapes like contrasted curves, smooth curves and also detects objects of same characteristic like colour, size, and shape. Temporal filtering algorithm rejects false detection by using motion coherence criterion. The detected scratches are corrected by exemplar-based inpainting. Then, for flicker correction, the unwanted change in image brightness is removed from each frame. Finally, the processed frames are combined together to generate the restored video.

A. *Spatial Filtering Algorithm*

Kokaram [2], was the first to propose a spatial model for detection of line scratches and it is based on the hypothesis that the "side lobes" are visible on either side of a scratch. Bruni et al. [3] provides an explanation that side lobes are caused by light diffraction during the film scanning process. The same model is used in [4], this approach is considered to be among the most efficient for line scratch detection. In the other methods such as [5] and [6], scratches were detected in wavelet domain. These spatial algorithms have several weaknesses. Firstly, scratches are represented as straight vertical lines. Secondly, algorithms cope badly in noisy and textured areas. Finally, the detected line scratch covers the entire frame height.

The proposed spatial filtering algorithm relaxes some hypotheses found in previous algorithms and thus it can detect a variety of scratches. It composed of two steps: 1) Pixel-Wise detection and 2) Scratch pixel grouping and validation using a contrario methodology. The summary of the proposed spatial filtering algorithm is given in fig.1.

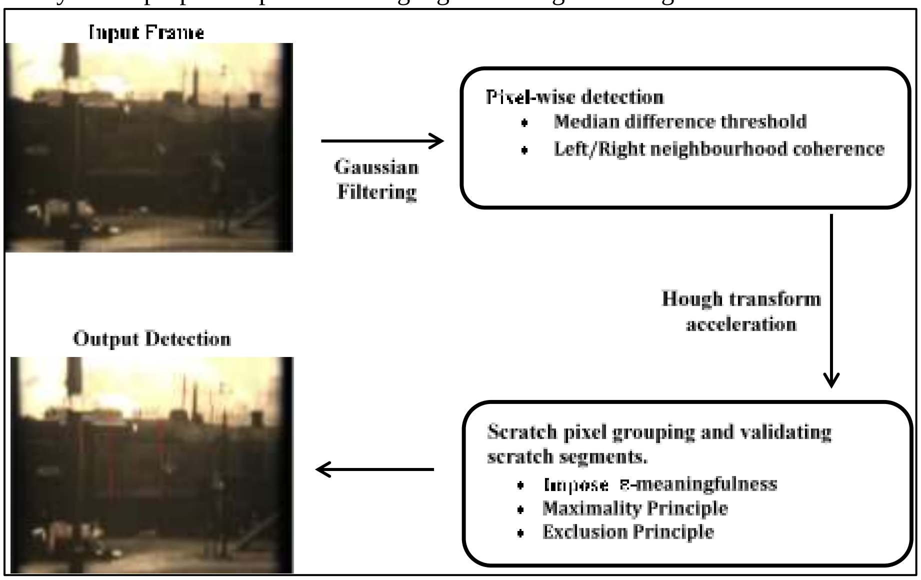

Fig. 1: Summary of the proposed spatial filtering algorithm

1) Pixel - Wise Detection

The potential scratch pixels are identified by pixel-wise detection criteria. This criterion is a close variant of the classical test introduced by Kokaram [2]. Contrary to this original criterion, the central pixel is not considered when determining the median value. Initially each frame is Gaussian filtered to reduce noise. The average grey level values on either side of the scratch should be similar in order to avoid steep intensity fronts.

The pixel-wise detection criterion can be explained by two Boolean criteria and they are given by:

$$c_1(x,y): \left|I_g(x,y) - I_m(x,y)\right| \geq s_{med,}$$
$$c_2(x,y): \left|I_l(x,y) - I_r(x,y)\right| \leq s_{avg} \quad (1)$$

Where Ig(x, y) be the Gaussian filtered grey level image, Im(x, y) represent the median value over a local horizontal neighborhood of pixel (x, y), Il(x, y) and Ir(x, y) be the left and right horizontal averages and smed and savg are grey-level thresholds.

Therefore a binary image, IB(x, y), indicating detection can be defined as:

$$I_B(x,y) = \begin{cases} 1, & if\ c_1(x,y) \ \ and \ \ c_2(x,y) \\ 0, & otherwise \end{cases} \quad (2)$$

Pixel-Wise detection criteria can be illustrated with fig. 2. In fig .2 the white pixels are the detected pixels and the black pixels are the ignored ones. As seen in fig.2, this step can produce many false alarms due to noise and texture; therefore it is followed by a grouping step to determine valid scratch segments.

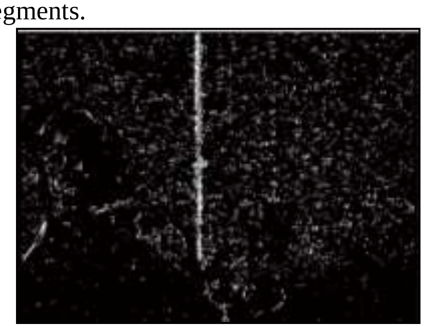

Fig. 2: Frame after pixel-wise detection

2) Scratch Pixel Grouping and Validation using a Contrario Methodology

In [7] and [8], Hough transform, is used to detect line segments in binary images but this approach contains threshold which need to be tuned from sequence to sequence. Therefore in order to group pixel-wise detection, a contrario methodology [10] is used. This methodology is used to detect visual objects in digital images. It mainly depends on the background model and the detection thresholds are set in order to control the number of false detection.

Here in this case, the basic elements to be grouped are pixels and segments are detected as group of pixels. A segment is said to be detected, if its gradient of orientation is perpendicular to a given direction. For a line segment made of l pixels, a variable xi is associated to each pixel and this variable xi is equal to 1 if the pixel is aligned and 0 otherwise. A pixel can align with the segment up to some angular precision of pπ radians. A segment, s can be represented as, s = x1 + x2 + …….+ xl , and the value of s increases for more meaningful line segments. The aim of a contrario methodology is to precisely set the detection threshold and these thresholds depend on the parameters l and p.

For a general case, for example, in a Gaussian white noise image, the background model specifies that all gradient orientations are independent and follow a uniform distribution. This hypothesis detects alignments mainly in homogenous regions, noisy regions, isotropic texture etc. Therefore for the present case a general background model would not be satisfactory. The difficulty is due to the fact that pixel-wise detection produces an amount of false detection. It produces more detection in strongly textured or cluttered areas than smooth regions.

So, now the background model is considered to be a binary image in which labels are independent and label probability of each pixel varies spatially. The probability for given pixel is estimated as the maximum detection density. Detection density is defined as the amount of pixel, contained within a square, whose labels equal 1. Now the probability for a given segment to have at least k_o aligned pixels is given by Poisson Binomial distribution. The direct computation of this probability is difficult and therefore an approximation is needed, which is referred to as Hoeffding's inequality [9]. The approximation probability, $P_r(S_l \geq k_0)$ is given by:

$$P_r(S_l \geq k_0) \leq H(l, k_0) := e^{-l\left(r\log\frac{r}{<p>}+(1-r)\log\frac{1-r}{1-<p>}\right)} \qquad (3)$$

Where, S_l is the number of pixels having a label value of 1 along a segment of length l, $\langle p\rangle = l^{-1}\sum p_i$ is the average detection probability of a segment, for k_0 aligned pixel $r = k_0 / l$ and $\langle p\rangle l < k_0 < l$.

Therefore the number of false alarm, NFA of a segment is given by:

$$NFA(l, k_0) = N_{tests} H(l, k_0) \qquad (4)$$

Where N_{tests} is the number of segments to be tested. N_{tests} is set to $M^2N\theta$, where θ is the number of angles tested. $H(l,k_0)$ is the Hoeffding's inequality. A segment is said to be detected if its NFA is smaller than Ɛ and such a segment is referred to as 'Ɛ-meaningful'. The condition for such a segment is given by:

$$NFA(l, k_0) \leq \varepsilon \qquad (5)$$

- Maximality: With previous methods, many redundant segments are detected. To keep the best detection, we use maximality [10]. A segment is said to be maximum meaningful if it neither contains, nor is contained, by a segment which is more meaningful. Such segments would start with detected pixel preceded by an undetected pixel and end similarly.
- Exclusion Principle: Scratches can have a width of several pixels. For restoration purpose the scratches are precisely represented, for that exclusion principle [9] is being used. It states that a pixel may belong to one scratch only. If a pixel is contained by several segments, then the more meaningful segment retains the pixel and all other segments which contain the pixel have this pixel removed. The NFAs of the modified segment recalculated and those segments which are no longer Ɛ-meaningful are rejected.
- Hough Transform: A pre-selection of scratches candidates is done to speed-up the procedure. For that a very permissive Hough Transform is applied to binary detection image, IB(x,y) and analyse the lines which correspond to local maxima. This speed-up procedure was previously used in [7], [8].

There are two main differences between the proposed work and the work proposed by Kokaram [2]. Firstly, a contrario step does not require a scratch profile model. Secondly, this method looks for best sub-segment in a line. Fig.3 represent the output for spatial filtering algorithm, the eight red lines shows the detected scratch segments.

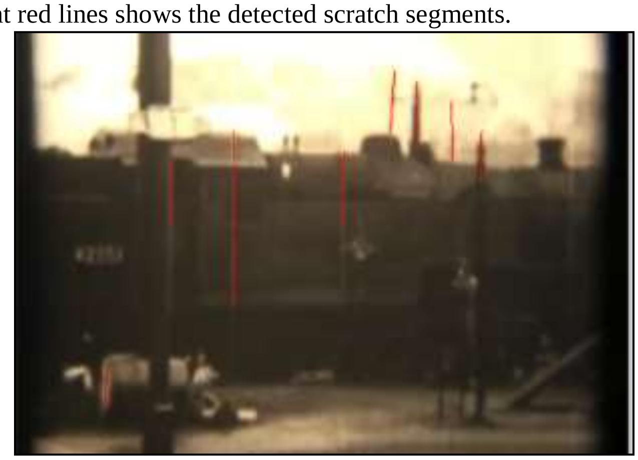

Fig. 3: Frame after spatial filtering algorithm

B. *Temporal Filtering Algorithm*

The spatial filtering algorithm detects line scratches with good spatial precision. It does not deal with the problem of false alarms caused by the thin vertical structures that are part of the captured scene. Temporal approaches may be found from [11]- [15]. The goal of these algorithms is to validate the detections based on the temporal nature of line scratches. The basic concept of [15], motion of an object is completely independent from the background scene is used in this approach. So, any detection showing motion which is coherent to the background scene corresponds to false detection and such detections would be rejected. This criterion is referred to as motion coherence criterion. For that the original positions of the segment in the trajectory set is determined utilizing horizontal motion of the scene. Consider two segments Q and R belonging to a trajectory set and verify the following inequality:

$$|\tilde{x}(Q) - \tilde{x}(R)| \geq \tau_m \qquad (6)$$

Where τ_m is a motion threshold. This inequality corresponds to the absolute distance the scene has moved between the frames t(Q) and t(R). If the value is greater than the threshold τ_m, then such a trajectory set would be rejected.

As seen in fig.3, eight line scratches were detected by spatial filtering algorithm and after temporal filtering algorithm it has been reduced to three. Thus out of eight detected scratch segments five of them corresponds to false detection and it was effectively removed by temporal filtering algorithm. Fig.4. shows output after temporal filtering algorithm.

Fig. 4:.Frame after temporal filtering algorithm

C. *Scratch Removal by Inpainting*

Scratch removal is done by exemplar-based inpainting. The scratches in each frame is identified as the target region, Ω, which is to be removed and filled. Its contour is denoted by δΩ and it evolves inward as algorithm progresses. It is also referred to as "fill front". The source region, Φ remains fixed and provides with samples used in filling process. Fig.5 represent the output after inpainting. The algorithm is referred to as Region – filling algorithm and it iterates the following three steps until all pixels have been filled.

1) Computing patch priorities of each patch

Algorithm depends on the priority value assigned to each patch on the fill front. Its computation is biased towards those patches which are on the continuation of strong edges and which are surrounded by high – confidence pixels. The priority *P(p)* for a patch Ψ_p centered at point p for some p ϵ δ Ω is given by -

$$P(p) = C(p)D(p) \qquad (7)$$

Where *C(p),* represent the confidence term , and *D(p),* represent the data term. Confidence term *C(p),* is a measure of reliable information surrounding the pixel p. During initialization, the confidence term, *C(p)=0*, for target region, Ω and *C(p)=1*,for the source region Φ. Data term *D(p),* determine the strength of isophotes hitting the fill front at each iteration. It boosts the priority of a patch that an isophote flows into and they are defined as follows:

$$C(p) = \frac{\sum_{q \in \Psi_p \cap \bar{\Omega}} C(q)}{|\Psi_p|} \qquad 7(a)$$

$$\mathrm{D(p)} = \frac{|\nabla \mathrm{I_p}^{\perp} . \mathrm{n_p}|}{\alpha} \qquad 7(b)$$

Where $|\Psi_p|$ is the area of Ψ_p, α is a normalization factor, n_p is a unit vector orthogonal to the contour $\delta\Omega$ of the target region Ω in the point p and $\nabla I_p{}^{\perp}$ is the isophote at point p, *I* represent original image. The notation diagram is given by fig.5.

2) Propagating texture and structure

A patch $\Psi_{\hat{p}}$, with highest priority is found and then fill it with data extracted from the source region Φ. For that, in the source region search for the patch which is most similar to $\Psi_{\hat{p}}$ and such an exemplar is given by$\Psi_{\hat{q}}$.

$$\Psi_{\hat{q}} = \arg\ min\ d(\Psi_{\hat{p}}, \Psi_q) \ \ , \ \Psi_q \in \Phi \qquad (8)$$

3) Update confidence value

After the step 2, patch ,$\Psi_{\hat{p}}$ has been filled with new pixel values. Now the confidence *C(p)* is updated in the area delimited by $\Psi_{\hat{p}}$ and is given by:

$$C(q) = C(\hat{p}) \qquad \forall q \in \Psi_{\hat{p}} \cap \Omega \qquad (9)$$

(a) (b) (c)

Fig. 5: (a) Notation diagram for exemplar-based inpainting (b) Scratches(target region) removed for inpainting (c) Frame after inpainting

D. Correction of Intensity Flicker

Image flickering is defined as the unnatural temporal fluctuations in perceived image intensity. It does not originate from the original scene. Therefore obtaining useful information from old video affected by flicker is a difficult task. For flicker correction, a flicker window, w, of appropriate size is chosen. Flicker window is chosen based on the amount of flickering. A threshold value is employed to detect flickers and avoid non-flicker region being corrected. Finally, mutual information and joint entropy are computed for performance evaluation. Mutual information is a measure of similarity between images and where it assumes that there is no prior functional relationship between images. Mutual information and joint entropy is inversely propotional. These values are computed for both inpainted frame and, inpainted and flicker corrected frame, with that of the original frame.The values are listed in Table 1. From the listed value we can infer that the flicker correction was able to remove the image brightness fluctuation effectively. The frame after inpainting and flicker correction is given by fig.6.

Fig. 6: Frame after inpainting and flicker correction

Table - 1
Performance Evaluation

Input frame	*Mutual Information*	*Joint Entropy*
Inpainted frame	*6.9612*	*7.3221*
Inpainted and flicker corrected frame	*6.3818*	*7.9610*

III. CONCLUSION

In this paper we have presented precise video restoration algorithms. Spatial filtering algorithm and temporal filtering algorithm is used to detect line scratches. The spatial algorithm uses a contrario validation step to determine if the detected segments are visually significant or not and temporal filtering step eliminates false detection. These algorithms provide a precise description of the detected scratches. The removal of detected scratches and intensity flicker improve the subjective quality of the old film sequences. Evaluations were carried out without any sequence – dependent tuning, which illustrates the robustness of the algorithms.

ACKNOWLEDGMENT

I acknowledge my gratitude to all other faculty members of the Department of Electronics and Communication Engineering for their whole hearted cooperation and encouragement.

REFERENCES

[1] Alasdiar Newson, Andres Almansa, Yann Gousseau and Patrick Perez, "Robust Line Scratch Detection in Films", IEEE Trans. Image Proc. vol. 23, no. 03, March 2014.
[2] A. Kokaram, "Detection and removal of line scratches in degraded motion picture sequences," Signal Process., vol. 1, no. 9, pp.5–8,Sep. 1996.

[3] V. Bruni, D. Vitulano, and A. Kokaram, "Line scratches detection and restoration via light diffraction," in Proc. 3rd Int. Symp. Image Signal Process. Anal., vol. 1. 2003, pp. 5–10.
[4] A. Desolneux, L. Moisan, and J. M. Morel, "Meaningful alignments," Int. J. Comput. Vis., vol. 40, no. 1, pp. 7–23, Oct. 2000.
[5] T. Bretschneider, O. Kao, and P. J. Bones, "Removal of vertical scratches in digitised historical film sequences using wavelet decomposition," in Proc. Image Vis. Comput. New Zealand, Nov. 2000, pp. 38–43..
[6] S. Müller, J. Bühler, S. Weitbruch, C. Thebault, I. Doser, and O. Neisse,"Scratch detection supported by coherency analysis of motion vector fields," in Proc. 16th IEEE Int. Conf. Image Process., Nov. 2009, pp. 89–92.
[7] A. Kokaram, "Detection and removal of line scratches in degraded motion picture sequences," Signal Process., vol. 1, no. 9, pp. 5–8, Sep. 1996
[8] K. Chishima and K. Arakawa, "A method of scratch removal from old movie film using variant window by Hough transform," in Proc. 9th Int. Symp. Commun. Inf. Technol., 2009, pp. 1559–1563.
[9] W. Hoeffding, "Probability inequalities for sums of bounded random variables," J. Amer. Statist. Association, vol. 58, no. 301, pp. 13–30, Mar. 1963.
[10] A. Desolneux, L. Moisan, and J. M. Morel, "Meaningful alignments," Int. J. Comput. Vis., vol. 40, no. 1, pp. 7–23, Oct. 2000.
[11] M. K. Gullu, O. Urhan, and S. Erturk, "Scratch detection via temporal coherency analysis and removal using edge priority based interpolation," in Proc. IEEE Int. Symp. Circuits Syst., May 2006, pp. 4591–4594.
[12] L. Joyeux, S. Boukir, and B. Besserer, "Film line scratch removal using Kalman filtering and Bayesian restoration," in Proc. 15th IEEE Workshop Appl. Comput. Vis., Dec. 2000, pp. 8–13.
[13] L. Joyeux, S. Boukir, and B. Besserer, "Tracking and MAP reconstruction of line scratches in degraded motion pictures," Mach. Vis. Appl., vol. 13, no. 3, pp. 119–128, 2002
[14] L. Joyeux, O. Buisson, B. Besserer, and S. Boukir, "Detection and removal of line scratches in motion picture films," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 1999, pp. 548–553
[15] S. Müller, J. Bühler, S. Weitbruch, C. Thebault, I. Doser, and O. Neisse, "Scratch detection supported by coherency analysis of motion vector fields," in Proc.16th IEEE Int.Conf. ImageProcess., Nov.2009,pp.89–92.