INTERPOLATION OF SCRATCHES IN MOTION PICTURE FILMS

T. Bretschneider [1], *C. Miller* [2], *O. Kao* [1]

[1] Department of Computer Science,
Technical University of Clausthal, Germany
[2] Department of Electrical and Electronic Engineering
University of Canterbury, New Zealand

ABSTRACT

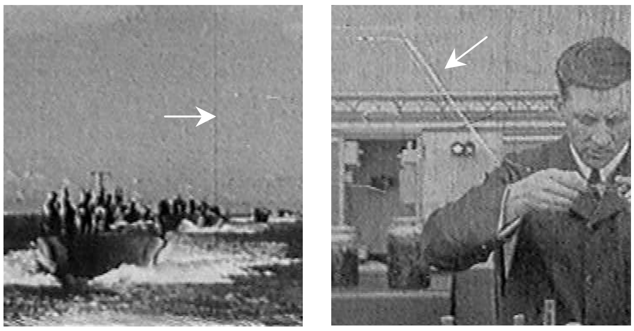
Movie films are often damaged through ageing, chemical changes and contact with mechanical parts of a film projector. In this paper a method for the removal of scratches and undesirable lines in digitised film sequences is discussed. The method assumes the prior knowledge about the position and orientation of the scratches and utilises an iterative method to interpolate the affected pixels. The convergence of the algorithm is guaranteed for the noise free case and the optimal choice of the involved relaxation parameter is demonstrated. The method was validated using sampled movies and proved to be stable even in the presence of noise. Remarkable is the reconstruction result in comparison to standard interpolation techniques like cubic splines.

1. INTRODUCTION

Movie films are often damaged through ageing, chemical changes and abrasion by contact with mechanical parts of a film projector. The reconstruction of already damaged material and preservation of the movie heritage is an important task, but manual restoration is expensive in time and money due to the huge data volume. Therefore unsupervised processing methods for removal of frequently occurring defects are highly desirable.

In this paper a method for the removal of scratches and lines is discussed. Scratches are a frequently occurring defect in old movies and are caused by careless handling of the film material, for example by contact of the film material with a mechanical part of the film projector. A part of the film surface, i.e. the emulsion, is lost and the result is a scratch often visible over a number of frames. The bright or dark characteristic of the scratch is related to the type of film material, i.e. whether it is a positive print or a negative. The analysis of film material sampled to the European standard television broadcasting norm (PAL: 768×576 pixels) has shown that the typical scratch is approximately five pixels wide. Although the width of a scratch is small, the attention of the observer is attracted by the strong discontinuity. Another type of distortion with the same characteristic for the observer's eye are undesirable lines in copies of old movies caused by the contamination of the original film with dirt particles, e.g. hairs. Fig. 1 shows single frames out of two sequences with scratches due to abrasion of the emulsion.

The problem of scratch removal has been addressed in numerous papers. Standard techniques [1], [2] are based on variations of the spatio-temporal mean and median filters restricted to local regions of interest. These methods are straightforwardly implemented and involve only a modest computational load. Although the result is satisfying for a still image, in a film sequence the lack of texture due to the employed reconstruction method is noticeable as a blurring. In the case of vertical scratches due to abrasion by contact with mechanical parts the effect is emphasised by the fact that the distorted region does not move. Other algorithms using nonlinear operations [3], adaptive multidimensional prediction [4], min-max functions [5], and Fourier series with parameter estimation in a local neighbourhood [6] have been suggested, but none have been found to be totally satisfactory.



(a) (b)

Fig. 1. Degraded film frames: (a) frame with vertical scratch, (b) frame with diagonal scratch.

The main problem is the reconstruction of higher frequency components. This paper proposes a scratch removal technique based on an iterative reconstruction method. To overcome the difficulty of convergence in the case of noise the incorporation of adjacent frames can drop the noise level and therefore stabilise the result. Note the need for a prior motion, zoom, and pan compensation.

The example images in this paper are monochromatic. While the majority of old movie films are black-and-white, it is straightforward to apply the technique to colour films. For the multispectral case the Karhunen-Loeve transformation [7] may be used to minimise the correlation between the spectral bands. Thereby each band may be individually processed using the proposed technique. The corresponding inverse transformation produces the reconstructed multispectral film sequence.

2. METHOD

The idea of the presented method is similar to the Gerchberg-Papoulis algorithm [8], [9] which was proposed for the extrapolation of band-limited signals with a known support. The method is based on the successive imposition of the compact support constraint upon the solution in the signal domain and the imposition of the known samples in the Fourier domain. In this paper the concept of reversing the two constraints is utilised, i.e. the Fourier transform of the data is band-limited and known samples are superimposed in the signal domain. For convenience the problem is herein after treated as an one-dimensional problem of signals taken perpendicular to the main extent of the scratch. Therefore the number of missing samples in a sequence is minimised and the process stabilised.

2.1 Model

The model for sampling a movie m is depicted in Fig. 2. The pairs (x,y) and (n,k) represent continuous and discrete coordinates respectively.

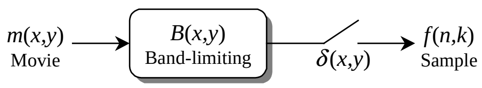


Fig. 2. Model for the sampling of a movie.

The band-limiting B is necessary to avoid aliasing in f and the sampling process δ has to be chosen with respect to B. A signal f is band-limited if its energy is finite and its Fourier transform (FT) F is zero for frequencies above a cut-off frequency σ, i.e.

$$F(\omega) = \mathrm{FT}\{f(t)\} = 0 \quad \forall|\omega| > \sigma. \tag{1}$$

For convenience it is assumed that the entire model can be expressed digitally and that prior knowledge of which samples are affected by the distortion [2], [6], [10] is available. The corresponding model for the scratching and reconstruction is shown in Fig. 3. In the following all coordinate indices are dropped.

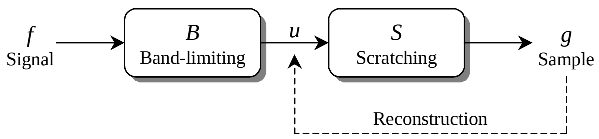


Fig. 3. Degradation and reconstruction model.

According to Fig. 2 f has already been band-limited due to the avoidance of aliasing in the sampling process and therefore B has no influence on f. However, B is needed as a constraint on the solution space in the reconstruction process since the scratching S introduces high frequency components in g. Using algebraic notation the process in Fig. 3 can be described by

$$g = SBf + n, \tag{2}$$

where n accounts for noise. Note that subsequently the emphasis is on the reconstruction of u to revert the scratch process.

2.2 Reconstruction

The reconstruction process estimates u using the available sample sequence g with components $g_0, g_1, \ldots, g_{N-1}$, the knowledge about the position of affected samples in g, i.e. S, and the band-limiting operation B. Thus with respect to the Landweber iteration [11] the reconstruction process using algebraic notation can be described by

$$\hat{f}_{l+1} = \hat{f}_l + \mu\left(g - SB\hat{f}_l\right). \tag{3}$$

This iterative solution is used to avoid the ill-posed nature of the direct solution. Multiplication of Equation (3) with B on both sides leads to

$$B\hat{f}_{l+1} = B\hat{f}_l + \mu\left(Bg - BSB\hat{f}_l\right) \tag{4}$$

and can be simplified using

$$\hat{u}_l = B\hat{f}_l \tag{5}$$

to get the Equation

$$\hat{u}_{l+1} = \hat{u}_l + \mu B\left(g - S\hat{u}_l\right) \tag{6}$$

where B is the band-limiting matrix, S the sampling matrix, and μ the relaxation parameter. The matrix B is given by $B=F^{-1}\Omega F$ with the Fourier matrix F as

$$F_{mk} = \frac{1}{\sqrt{N}} \exp\left(j2\pi \frac{mk}{N}\right) \quad \forall m,k \in \{0,1,\ldots,N-1\}. \tag{7}$$

Note that F is unitary and thus $F^{-1} = \overline{F}^T$. The matrix Ω consists of ones along the main diagonal for frequencies which are passed (with respect to the band-limit ω in Equation (1)) otherwise of zeros. The sampling matrix S is constructed similar to Ω and contains only zeros and ones on the diagonal according to the positions of missing and available values, respectively.

2.3 Convergence

Characteristically the process in Equation (6) converges rapidly at first and then more and more slowly as the limit is approached. An extensive understanding of the convergence can be gained by an eigenvalue analysis of the composition of the matrices B and S. While prior knowledge about S is available due to the scratch detection process [2], [3], [6], [10], this is often not true for B since the correct band-limit and shape of the filter used prior to the downsampling are unknown. Therefore this paper suggests an estimation process of the band-limit which assumes the signal to be statistically stationary in the local neighbourhood similarly to the hypothesis made in [5], [6]. The matrix B can be estimated for a completely known signal in the neighbourhood by minimising

$$\varepsilon_\omega(l) = \left\|u - \hat{u}_l\right\|^2 \tag{8}$$

for different band-limits ω. The method proved to be efficient enough for a reliable scratch interpolation using μ=1. However, if explicit knowledge about B is available then the optimal μ can be determined. In the following this is shown for the noise free case, i.e. $g=Su$. The estimate of u can be written as the sum of u and the estimation error e_l at the l^{th} iteration

$$\hat{u}_l = u - e_l. \tag{9}$$

Thus the combination of Equation (6) and (9) leads to

$$u - e_{l+1} = u - e_l + \mu B\left(Su - S\left(u - e_l\right)\right) \tag{10}$$

and hence

$$e_{l+1} = e_l - \mu BSe_l. \tag{11}$$

For simplicity of the notation let Q=BS. Writing e_{l+1} as column vector and using the Euclidean norm Equation (11) can be expressed by

$$\begin{aligned} \left\|e_{l+1}\right\|^2 &= e_{l+1}^H e_{l+1} \\ &= \left(e_l - \mu Qe_l\right)^H \left(e_l - \mu Qe_l\right) \\ &= e_l^H e_l - \mu e_l^H Qe_l - \mu e_l^H Q^H e_l + \mu^2 e_l^H Q^H Qe_l \\ &= \left\|e_l\right\|^2 - 2\mu \operatorname{Re}\left\{e_l^H Qe_l\right\} + \mu^2 e_l^H Q^H Qe_l \end{aligned} \tag{12}$$

where the superscript H indicates the Hermitian transpose. To prove the convergence, i.e.

$$\left\|e_{l+1}\right\|^2 \le \left\|e_l\right\|^2, \tag{13}$$

it has to be shown that

$$2\mu \operatorname{Re}\left\{e_l^H Qe_l\right\} \ge \mu^2 e_l^H Q^H Qe_l. \tag{14}$$

For this purpose an eigenvector analysis is applied where λ_i and v_i are the eigenvalues and eigenvectors of Q respectively. Therefore $|\lambda_i|^2$ and v_i are the eigenvalues and eigenvectors of $Q^H Q$. Using

$$\begin{aligned} e_l^H Qe_l &= \sum_i \lambda_i \left|e_l^H v_i\right|^2 \\ e_l^H Q^H Qe_l &= \sum_i \left|\lambda_i\right|^2 \left|e_l^H v_i\right|^2 \end{aligned} \tag{15}$$

Equation (14) can be rewritten as

$$2\mu \sum_i \lambda_i \left|e_l^H v_i\right|^2 \ge \mu^2 \sum_i \left|\lambda_i\right|^2 \left|e_l^H v_i\right|^2 \tag{16}$$

where the Re{·} function has been dropped since Q is Hermitian and thus all eigenvalues λ_i are real. Equation (16) is true if for all individual addends the inequality

$$2\mu\lambda_i \ge \mu^2 \lambda_i^2 \tag{17}$$

holds. Thus Equation (13) is valid if

$$0 \le \mu \le \frac{2}{\lambda_{max}} \tag{18}$$

where λ_{max} is the maximum eigenvalue of Q and the iterative process converges. Note that convergence might be achieved even if μ is not chosen with respect to Equation (18) since the criterion applied in Equation (16) is rather strict. However, convergence is always guaranteed if μ fulfils Equation (18).

The convergence of Equation (6) for two different choices of μ is depicted in Fig. 4 whereby μ=2/λ_{max} is the limit under which convergence is guaranteed. The solid curve shows the optimum convergence with μ_{opt}=1/λ_{max} which is computed by setting the derivative of Equation (17) equal to zero. Obviously the solution converges much faster for μ_{opt} while the choice μ=2/λ_{max} exhibits the weakest convergence possible. To start the iterative process the first estimate for u is assumed to be a uniform distributed sequence which is band-limited by B.

In the presence of noise the statistical properties of the noise have to be incorporated in the convergence analysis. However, experiences with the used film material indicate that the reconstruction process still converges for the existing noise level. Only in a few cases this is not guaranteed. As a consequence an additional constraint was added for real data which prevents the solution from divergence by imposing an upper and lower limit for the estimated values. If the limit is exceeded a cubic spline interpolation [12] is applied.

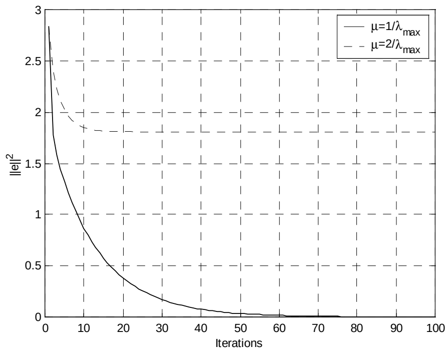


Fig. 4. Convergence of Equation (6) for two different choices of μ and a randomly generated Q.

3. RESULTS

Different influences on the reconstruction result for a known sequence u of 64 values were investigated. First the effect of additive white Gaussian noise on the reconstruction was studied. Fig. 5 shows the result with respect to the signal-to-noise ratio (SNR). Using the method proposed by Rank et al. [13] the SNR for the sampled frame displayed in Fig. 1(a) was estimated to be approximately 20dB which leads accordingly to Fig. 5 to a reasonable reconstruction result. However by averaging three adjacent frames after motion, zoom, and pan compensation the SNR can be improved to almost 35dB and thus leads to a far better restoration.

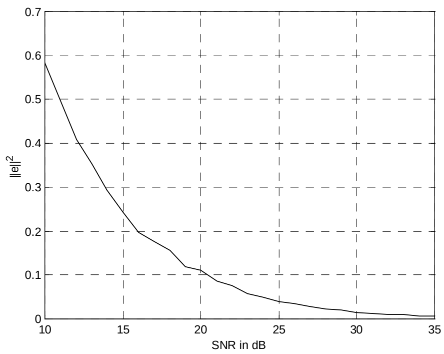


Fig. 5. Estimation of four missing values of the true signal u with respect to the SNR (additive white Gaussian noise).

In a second investigation the influence of the number of missing values was analysed to decide about the useability of the proposed method for interpolation of scratches in motion picture films. Fig. 6 displays the results for the number of missing pixels in the range from two to sixteen values. Note that the gap was always centred in the sequence of 64 values. Clearly the iterative interpolation is suitable for the scratch type under investigation with a typical width of approximately five pixels.

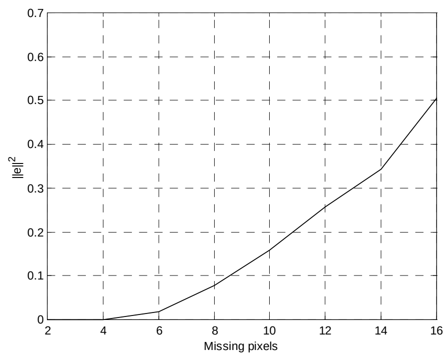


Fig. 6. Reconstruction error with respect to the number of missing values/pixels.

Finally Fig. 7 gives an example for the reconstruction of real imagery using the proposed algorithm. The image corresponds to an enlarged sub-image of Fig. 1(a).

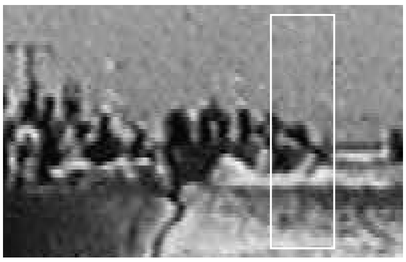


Fig. 7. Enlarged sub-image from the reconstruction of Fig. 1(a) with marked scratch region.

The proposed scratch removal method interpolates reliable missing pixels in historical motion picture films. Even for homogenous areas which exhibit a strong influence of noise to the observer, an almost perfect reconstruction is obtained without any blurring effect which was reported repeatedly for other methods [2], [3], [5].

4. CONCLUSIONS

In this paper a technique for removal of scratches in movies sampled to standard television broadcasting resolution was presented. The proposed iterative reconstruction method shows a good performance in the reconstruction of the image parts lost by the scratching. The result does not exhibit any blurring which frequently occurs for other interpolation techniques. Especially homogenous areas in the image which are mainly dominated by noise exhibit less artefacts which are typical for kernel-based interpolation methods.

Future work includes the incorporation of noise in the proposed model to improve the interpolation result and acceleration of the method using a direct, i.e. non-iterative, implementation.

5. ACKNOWLEDGMENT

This work has been partly supported by the German National Merit Foundation. The authors wish to express their thanks to Jan Engehausen for providing the motion picture frames used in this paper.

6. REFERENCES

[1] Abreu E., Mitra S.K. "A simple algorithm for restoration of images corrupted by streaks". *IEEE International Conference on Circuits and Systems*, 2:730-733, 1996

[2] Kao O., Engehausen J. "Scratch removal in digitised film sequences". *Proceedings of the International Conference on Imaging Science, Systems, and Technology*, pages 171-179, 2000

[3] Kim N.-D., Udpa S. "Nonlinear operations for edge detection and line scratch removal". *IEEE International Conference on Systems, Man, and Cybernetics*, 5:4401-4404, 1998

[4] Maindl M., Šimberová S. "A scratch removal method". *Kybernetika*, 34(4):423-428, 1998

[5] Armstrong S., Kokaram A., and Rayner P.J.W. "Non-linear interpolation of missing data using min-max functions". *IEEE International Conference on Nonlinear Signal and Image Processing*, July, 1997

[6] Joyeux L., Buisson O., Besserer B., and Boukir S. "Detection and removal of line scratches in motion picture films". *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1:548-553, 1999

[7] Pratt W.K.: *Digital Image Processing*. John Wiley & Sons, Inc., 2nd Edition, 1991

[8] Gerchberg R.W. "Super-resolution through error energy reduction". *Optica Acta*, 21:709-720, 1974

[9] Papoulis A. "A new algorithm in spectral analysis and band-limited extrapolation". *IEEE Transactions on Circuits and Systems*, 22:735-742, 1975

[10] Bretschneider T., Kao O., and Bones P.J. "Removal of vertical scratches in digitised historical film sequences using wavelet decomposition". *Proceedings of the Image and Vision Computing New Zealand*, 37-42, 2000

[11] Landweber L. "An iteration formula for Fredhold integral equations of the first kind". *American Journal of Mathematics*, 73:615-624, 1951

[12] Hou H.S., Andrews, H.C. "Cubic splines for image interpolation and digital filtering". *IEEE Transactions on Acoustics, Speech and Signal Processing*, 26(6):508-517, 1978

[13] Rank K., Lendl M., and Unbehauen R. "Estimation of image noise variance". *IEE Proceedings, Visual Image Signal Processing*, 146(2):80-84, 1999