

Fast Restoration of Colour Movie Scratches

Michal Haindl & Jiří Filip
Institute of Information Theory and Automation
Academy of Sciences of the Czech Republic
182 08 Prague, Czech Republic

Abstract

This paper presents a new type of scratch removal algorithm based on a causal adaptive multidimensional multitemporal prediction. The predictor use available information from the neighbourhood of a missing multispectral pixels due to spectral, temporal and spatial correlation of video data but not any information from the failed pixels themselves.

1. Introduction

A huge amount of documentary or artistic movies is stored in different film archives throughout the world. Unfortunately every movie deteriorates with usage and time irrespective of any care it gets. Movies (on both optical and magnetic materials) suffer with blotches, dirt, sparkles and noise, scratches, missing or heavily corrupted frames, mold, flickering, jittering, image vibrations and some other problems [12]. As a result of ever growing demand for archive movies there is the urgent necessity for movie restoration from film and entertainment industry. Surprisingly the number of published algorithms in the area of movie restoration is rather small probably because of computational complexity of most restoration approaches. For each kind of the defect usually different kind of restoration algorithm is needed. Our attention in this paper is restricted to the scratch restoration problem. The scratch notion in this paper means every coherent region with missing data (simultaneously in all spectral bands) in a colour movie frame.

The problem how to recover lost or damaged image data is old - since the dawn of photography to the digital images or movies obtained directly using CCD cameras, radiotelescopes [8], scanners on board of satellites, etc. The simplest methods neglect temporal correlation and reconstruct single movie frames separately. Such methods used to reconstruct image scratches are mostly very simple and the reconstruction quality is seldom satisfactory. In this paper we called these methods "classical" and they are used for

comparison. The simplest methods replace missing pixels by the local mean values (A), the median (B) or the motion compensated median [11]. Another method (C) linearly interpolates missing data using neighbours from both sides of unknown data section. These methods produce visible distortions on colour images. Even interpolation with higher order curves, such as quadratic fit, is of no help [2] - method (D). More sophisticated template-like methods suggested in [2] cannot be used for reconstruction of multi-spectral pixels with all spectral components missing what is the case of scratch reconstruction. Model-based methods use most often Markov random field type of models either in the form of wide sense Markov (regressive models) or strong Markov models (MRF). The noncausal regressive model used in [3],[4] has the main problem in time consuming iterative solution based on the conjugate gradient method. Similarly MRF based restoration methods [5], [9] require time consuming application of Markov chain Monte Carlo methods (MCMC). Besides this both approaches have to solve the problem when to stop these iterative processes. We have proposed a 2D regression model based reconstruction method [6], [7], which clearly outperforms these image reconstruction methods. The method was further improved in [8] to select a locally optimal predictor from two mutually competing symmetrical adaptive predictors for each pixel to be reconstructed. Similar 2.5D AR model was later used in [10], however its degradation model requires time consuming Markov chain Monte Carlo iterations and is restricted to monospectral movies only. Another method based on the vector median model [1] enables colour scratch reconstruction but has similar disadvantage in the MCMC solution.

An optimal reconstruction resulting in visual disappearance of the scratch is difficult to achieve, however a much more precise replacement beyond the scope the current methods is needed. From this originated an idea to reconstruct missing data from available information due to large correlation between single image elements in the 4D spatio-temporal data space. In this paper we propose a fast multispectral movie reconstruction method based on a causal 3.5D AR data model. The method reconstructs missing

multispectral (e.g., colour) pixels from available data in neighbouring frames and pixels from the corrupted frame as well. The algorithm requires information about objects motion between different movie frames, which is extensive research area itself beyond the scope of presented work. For our experiments we used the diamond search algorithm for fast block-matching motion estimation [13].



Figure 1. Experimental frames from the cars (left) and tennis sequences.

2. The 3.5D Image Model

Suppose Y represents a digitized colour movie defined on a finite rectangular four dimensional $N \times M \times d \times \tau$ underlying lattice I , where $N \times M$ is the frame size, d is the number of spectral bands (i.e., $d = 3$ for usual colour movies) and τ is the overall number of frames in the film to be reconstructed. Corresponding pixel multiindex $r = \{r_1, r_2, r_3, r_4\}$ has the row, columns, spectral and time indices, respectively. All image data are assumed to be known except a set (\mathcal{S}) of unobservable multispectral pixels from some frame belonging to a scratch. The missing scratch data reconstruction from the topologically nearest known data in the lattice I using temporal and spatial correlation in the neighbourhood generally requires a 4D model. Unfortunately parameters of such a AR model cannot be estimated analytically. However if we neglect mutual temporal correlations, i.e.,

$$E\{e_{r_1, r_2, r_3, \bullet} e_{s_1, s_2, s_3, \bullet}^T\} = \text{diag}[\sigma_{r_3}^2, \dots, \sigma_{r_3}^2]$$

$\forall s : s_1 = r_1, s_2 = r_2, s_3 = r_3$ but nevertheless use different temporal multispectral pixels in a 3D AR model we obtain the 3.5D AR model which can be solved analytically under some additional acceptable assumptions. The notation \bullet has the meaning of all possible values of the corresponding index. Suppose further that the multispectral multitemporal movie data can be represented by an adaptive causal 3.5 dimensional simultaneous autoregressive model:

$$Y_{r_1, r_2, \bullet, r_4} = \gamma X_{r_1, r_2, \bullet, r_4} + e_{r_1, r_2, \bullet, r_4} \quad \forall r \in I, \quad (1)$$

where $Y_{r_1, r_2, \bullet, r_4}$ is a multispectral $d \times 1$ vector corresponding to a single multispectral pixel in the r_4 -th frame,

$$X_{r_1, r_2, \bullet, r_4} = [Y_{r_1 - s_1, r_2 - s_2, \bullet, r_4 - s_4} : \forall \{s_1, s_2, s_4\} \in I_{r_1, r_2, r_4}]^T$$

$$\gamma = [A_1, \dots, A_\eta], \quad (2)$$

is a $d \times d\eta$ parameter matrix, $I_{r_1, r_2, r_4} \subset I$ is a contextual neighbourhood and $\eta = \text{card}\{I_{r_1, r_2, r_4}\}$. Data ordering in $X_{r_1, r_2, \bullet, r_4}$ corresponds to the arrangement of parameters in (2). The noise vectors $e_{r_1, r_2, \bullet, r_4}$ are assumed to be mutually uncorrelated zero mean white Gaussian, i.e.,

$$E\{e_{r_1, r_2, \bullet, r_4} e_{s_1, s_2, \bullet, s_4}^T\} = \begin{cases} 0 & \text{if } r \neq s \\ \Sigma & \text{otherwise} \end{cases}$$

where Σ is the noise covariance $d \times d$ matrix which is assumed to be constant but unknown to us.

The missing scratch data will be reconstructed from the topologically nearest known data in the lattice I using temporal and spatial correlation in the neighbourhood. Scratch pixels are computed from the set of one-step-ahead predictions using the conditional mean predictor

$$\tilde{Y}_r = E\{Y_{r_1, r_2, \bullet, r_4} | Y^{(r-1)}\} = \hat{\gamma}_{r-1} X_{r_1, r_2, \bullet, r_4}, \quad (3)$$

where $Y^{(r-1)} = \{Y_{r-1}, Y_{r-2}, \dots, Y_1\}$ is the known process history and $\hat{\gamma}_{r-1}$ is the estimator of unknown model parameter matrix γ (2). Simplified notation $r, r-1, \dots$ in (3) and the process history denotes the multispectral process position in I for fixed r_4 , i.e., $r = \{r_1, r_2, \bullet, r_4\}$, $r-1$ is the location immediately preceding r , etc. A direction of movement on the underlying image sub-lattice corresponding to a corrupted frame is chosen in a way to erode the frame scratch.

If we assume the normal-Wishart (or alternatively Jeffreys) parameter prior then it was proven in [6] that the one-step-ahead predictive posterior density to have the form of d -dimensional Student's probability density with $\beta(r) - d\eta + 2$ degrees of freedom, if $\beta(r) > d\eta$ then the conditional mean value is (3), where

$$\hat{\gamma}_{r-1}^T = V_{xx(r-1)}^{-1} V_{xy(r-1)}. \quad (4)$$

The following notation is used in (4):

$$\tilde{V}_{vw(r-1)} = \sum_{k=1}^{r-1} V_k W_k^T$$

and $V_{vw(r-1)} = \tilde{V}_{vw(r-1)} + V_{vw(0)}$. V_k, W_k are either X_k or Y_k and $\beta(r) = \beta(0) + r - 1 = \beta(r-1) + 1$, $\beta(0) > \eta - 2$, and $\lambda_{(r)} = V_{yy(r)} - V_{xy(r)}^T V_{xx(r)}^{-1} V_{xy(r)}$ (see [7] for details). The model adaptation is introduced using the standard exponential forgetting factor technique in the parameter learning part of the algorithm [7]. Let us assume a set of AR models $(1) M_1, M_2, \dots$ which can differ either in the contextual neighbourhood I_{r_1, r_2, r_4} or / and in

their exponential forgetting factor ρ . The optimal decision rule for minimizing the average probability of decision error chooses the maximum a posterior probability model, i.e., a model whose conditional probability given the past data is the highest one. The presented algorithm can be therefore completed [8] as:

$$\tilde{Y}_r^i = \tilde{\gamma}_{r-1}^{i,T} X_{i,r} \quad \text{if} \quad \begin{aligned} & p(M_i|Y^{(r-1)}) > p(M_j|Y^{(r-1)}) \\ & \forall j \neq i \end{aligned} \quad (5)$$

where $X_{i,r}$ are data vectors corresponding to I_{r_1, r_2, r_4}^i . Following the Bayesian framework, choosing uniform a priori model in the absence of contrary information, and assuming conditional pixel independence, the analytical solution has the form [8] $p(M_j|Y^{(r-1)}) = k \exp\{D_j\}$, where

$$\begin{aligned} D_j = & -\frac{d}{2} \ln |V_{xx(r-1)}| - \frac{\beta(r) - d\eta + d + 1}{2} \ln |\lambda_{(r-1)}| \\ & + \frac{d^2 \eta}{2} \ln \pi \sum_{i=1}^d \left[\ln \Gamma\left(\frac{\beta(r) - d\eta + d + 2 - i}{2}\right) \right. \\ & \left. - \ln \Gamma\left(\frac{\beta(0) - d\eta + d + 2 - i}{2}\right) \right] \end{aligned} \quad (6)$$

and k is a common constant. All statistics related to a model M_j $\tilde{V}_{xy(r-1)}, \tilde{V}_{xx(r-1)}$, (10) are computed from data in $X_{j,r}$. The determinant $|V_{xx(r)}|$ as well as λ_r can be evaluated recursively see [7]. If $A_i = \text{diag}[a_{1,i}, \dots, a_{\nu,i}] \forall i$ then the 3.5D model reconstruction is identical with separately applied 2.5D model reconstruction on every monospectral scratch pixel component.

Let's assume a model movement towards the scratch. When the model reaches the scratch, the corrupted pixel prediction is evaluated. This is performed for each line in the scratch from top and bottom edge of the scratch using two symmetrical downwards and upwards moving models and their results are averaged. This helps to counterbalance artificial restriction on the contextual neighbourhood which has to be causal. Similarly another couple of models is moving in the opposite direction. Two computed predictions for each missing pixel have to be combined. Simple averaging is not appropriate, because each of both predictors has different distance from the last known original data and consequently it has also a different precision. Hence the exponential interleaving was used to weight the data influence from each side of the scratch as a function of the horizontal position of the predicted pixel on a scratch line to be reconstructed.

3 Results and Conclusions

The performance of the methods is compared on artificially created scratches, so that the original ("ideal") data

are known. To prevent subjective visual comparison of the different methods results the mean absolute difference criterion between original and replaced pixel values is used.

$$\overline{MAD} = \frac{1}{\nu d} \sum_{i=1}^d \frac{1}{\xi_i} \sum_{r \in \mathcal{S}} |Y_{r_1, r_2, i, r_4} - \tilde{Y}_{r_1, r_2, i, r_4}|,$$

where $\nu = \text{card}\{\mathcal{S}\}$ is the number of missing multispectral scratch pixels and ξ_i ($\xi_i = 255 \forall i$ in our test movies) is the number of quantization levels in the i -th spectral band.

All evaluations are made on several frames (e.g., Fig.1)

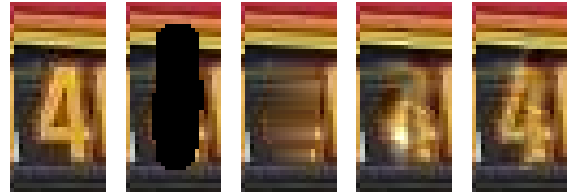


Figure 2. A car frame restoration (original, scratch, C method, 3D CAR, 3.5D CAR).

from two colour digital movies "cars" and "tennis". All selected frames are inside corresponding movie shots hence they have correlated neighbouring frames needed for the 3.5D presented data model. The model can be easily simplified into a 3D version (the multiindex has only three indices $r = \{r_1, r_2, \bullet\}$, I_{r_1, r_2}) and the scratch reconstruction is based on the reconstructed frame data only. Restoration results of 3D CAR and 3.5D CAR model are affected by the contextual neighbourhood I_r , by the exponential forgetting factor ρ , and by the length of the model history. The contextual neighbourhood has to be causal (in the reconstructed frame lattice I subspace) to get analytical solution for the predictor and its cardinality influences computational complexity of the overall algorithm - the smaller cardinality I_r has, the faster is the proposed method. Comparison results of the previously mentioned classical methods tested on the cars sequence frame are in Tab.1. The best results were obtained by the method C with contextual neighbourhood of two pixels on each side of a scratch. Both methods A and B suffer with clearly visible blurring tendency, while the methods C and D produce discernible columns in the reconstructed scratch. A significant improvement of the 3D model performance is obtained if the temporal information is included, i.e., using the 3.5D CAR model. Such information is natural to obtain from previous or / and following frame(s) for which we know all necessary data, due to high between-frame temporal correlation. Unfortunately it is not possible to simply pick up other frames data from the location corresponding to a reconstructed pixel in the 3.5D model, because of the motion present in the image sequence. So a motion estimation is needed between suc-

Table 1. Results (\overline{MAD} criterion) of basic image restoration method on the cars sequence frame corrupted by scratch on Fig.2

spectral band	method					
	A	B	C	D	3D	3.5D
Red	0.228	0.250	0.208	0.239	0.149	0.092
Green	0.202	0.218	0.168	0.210	0.138	0.087
Blue	0.119	0.120	0.092	0.124	0.115	0.071
average	0.183	0.196	0.156	0.191	0.134	0.083

cessive frames if a speed of the object on the reconstructed scene is faster than 2-3 pixels between neighbouring frames.

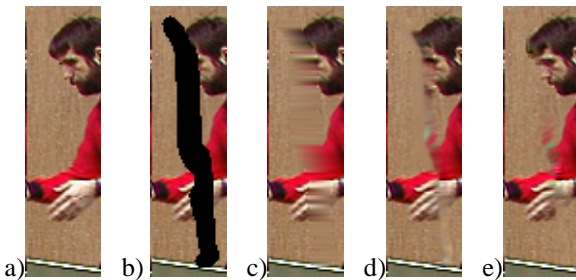


Figure 3. Scratch Fig.3-b) restoration in the 78th “tennis” (original (a), scratch (b), lin. regression (c), 3D CAR model (d), 3.5D CAR model (e)).

The motion estimation was performed by the method [13], however this algorithm demands more computation and prolongs the total time for restoration approximately five times in comparison with a 3D model. The motion estimation method results were sometimes unsatisfactory so for fully automatic restoration a better method is clearly required.

Because the exponential forgetting factor ρ directly influences the process memory (and the speed of adaptation). The best values for tested scratches are $\rho = 0.980 - 0.995$. The Fig. 3 example demonstrates significant reconstruction improvement over the classical methods (Tab. 1) and similar results were obtained also for the other experimental image frames. The test results of our algorithm are encouraging, the presented model was always superior over the classical methods not only using the \overline{MAD} criterion but also visually. For sequences with fast moving objects, the method requires a fast and accurate motion detection which is only partially solved problem itself. However even if the reliable motion estimation is missing the method can be easily restricted to single frame support data with slightly compromised restoration quality. Finally if the method is used for isolated image pixels (or short lines perpendicular to the model movement) reconstruction then the predictor is computed from completely known data (without any ap-

proximation) and the regression method performs much better than any of the previously published classical methods. The proposed method is fully adaptive, numerically robust and still with moderate computation complexity so it can be used in an on-line image acquisition / restoration system.

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