

# Deterioration Detection in a Sequence of Large Images

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## Abstract

*This paper presents a robust technique to detect local deteriorations of old cinematographic films. This method relies on spatio-temporal informations and combines two different detectors : a morphological detector which uses spatial properties of the deteriorations to detect them, and a dynamic detector based on motion estimation techniques. Our deterioration detector has been validated on several film sequences and turned out to be a powerful tool for digital film restoration.*

## 1. Introduction

Most of the techniques in use today for cinematographic film restoration are based on chemical and mechanical manipulations. Applying digital techniques to the field of film restoration let us expect results beyond today's limitations such as automated processing, correction of photographed dust spots and scratches (i.e. after film duplication), the removal of large defects, etc.

Our research institute is involved, beside the Laboratoires Neyrac Films company, in the European LIMELIGHT project which aims at designing a complete digital processing chain suitable to restore old films (film scanner, processing workstation, imaging device). Our main work concerns software development for automatic detection of defects like dust spots, hair and small scratches ).

Because the processed picture will be imaged back to film, preserving the visual quality in the software process is essential. Thus, the scanning provides high resolutions images (2200 x 1640 pixels or 4000 x 3000 pixels). Of course, these resolutions are uncommon in classical computer vision problems. This involves great difficulties especially when financial viability is aimed at by user of the LIMELIGHT chain. Keeping the processing time short is a significant problem which requires very fast algorithms.

Many approaches on defects restoration can be found in previous papers [4], [6]. In these works, the authors consider the "blobs" as impulse distortions or noise. Thus, deteriorations are restored using filtering techniques. These "blind" filters are applied to the entire image, removing deteriorations, but also deteriorating the regions which are not corrupted. A solution to cope with this problem consists in isolating first the regions with defects and then treating only these regions [7]. The following sections describe our detection algorithms.

## 2. Dust and scratch detection based on a single image

What are the origins of a dust or hair that is visible on an image ? Mainly, it is a dust particle on the film which shades light during film-to-film copy operation or during film scanning. By the use of a specific high-tech film scanning device, ensuring a high resolution (less than 10  $\mu\text{m}$ , approximately the film grain size), the digital "signature" left by a dust particle is slightly different from photographed detail of the image, even a sharp, defined one (light dispersion within the sensitive layers). Overall, the characteristics of the defects tend to be :

- Small surface (varying from 1 to 50 pixels, which is small in a 2200 x 1640 image),
- The edges of defects have strong gradients.

### 2.1. Gray scale morphology

The four fundamental binary morphological transformations (erosion, dilatation, closing and opening) are all extended to gray scale morphology, without thresholding, via the use of local maximum and minimum operations.

Given a gray scale image,  $I$ , and a structuring element (SE),  $B$ , the following neighbourhood operators  $\oplus$  and  $\ominus$  form the basis of classical mathematical morphology [8], [9], [11] :

$$\begin{aligned} I(x, y) \oplus B &= I(u, v): \text{MAX}_{B(x, y)}(I(u, v) - B(u, v)) && \text{Dilatation} \\ I(x, y) \ominus B &= I(u, v): \text{MIN}_{B(x, y)}(I(u, v) + B(u, v)) && \text{Erosion} \\ (I(x, y))^B &= (I(x, y) \oplus B) \ominus B && \text{Closing} \\ (I(x, y))^B &= (I(x, y) \ominus B) \oplus B && \text{Opening} \end{aligned}$$

## 2.2. A morphological detector of local deteriorations

The closing operator has the attractive propertie of deleting local minima. Therefore, we can use it to detect black deteriorations. Similarly, the opening operator appears well suited to the detection of white deteriorations. Both morphological detectors of black and white deteriorations are then expressed as a simple difference between successive closing operations (or successive opening operations) and the original image :

$$D_{Black}(I(x, y), B_0, B_n) = (((I(x, y) \oplus B_0) \oplus B_n) \ominus B_n) \ominus B_0 - I(x, y)$$

$$D_{White}(I(x, y), B_0, B_n) = I(x, y) - (((I(x, y) \ominus B_0) \ominus B_n) \oplus B_n) \oplus B_0$$

Where SE  $B_0$  and  $B_n$  are defined as :

$$B_0 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad B_n = \begin{bmatrix} 2n & 2n & 2n & 2n & 2n \\ 2n & n & n & n & 2n \\ 2n & n & 0 & n & 2n \\ 2n & n & n & n & 2n \\ 2n & 2n & 2n & 2n & 2n \end{bmatrix}$$

The use of multiple SE  $B_0$  and  $B_n$  permits to take into account the slope  $n$  of image curve gradients. Indeed, defects are generally characterized by very strong gradients. On the other hand,  $B_0$  allows the detection of defects having smoothest gradients. For example, figure 2 left shows the result of the deteriorations detection using  $n=0$  on the image depicted on figure 1. We can notice that for  $n=0$ , i.e. without integrating curve gradient properties, the defect profiles are hardly distinguishable from their neighbourhood profiles.

On the contrary, using  $n=30$ , no ambiguity remains between peaks corresponding to "real" defects and other peaks (see figure 2 right). This result is very satisfactory and demonstrates the robustness of our morphological defects detector.

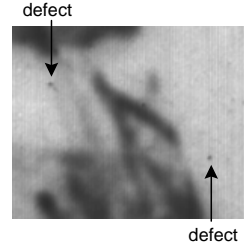


Figure 1: An ambiguous image part

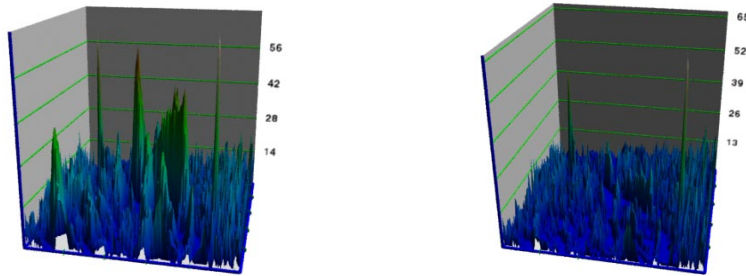


Figure 2 : Defects detection using  $n=0$  (left) and detection using  $n=30$  (right)

## 3. A dynamic detector of local deteriorations

Working on digitized film sequence gives us a great advantage, because we can use the information on the preceding and following frames. Our second defects detection algorithm uses this spatio-temporal information.

Unlike long linear scratches, dust particles appear in a random manner. However, we can't use simple frame subtraction or "XORing" to detect them, because, within a sequence, camera and actors or scene elements move around, objects may overlap other objects and/or background details (so-called occlusions or disocclusions).

Our dynamic detector relies on both motion-flow estimation and grey-level conservation. There are two main methods to estimate the optical flow of a "noisy" sequence of images :

- pre-filter the "noisy" sequence and use a classical motion estimation (block matching, regression, etc.).
- develop a motion-estimation algorithm which is robust to noise or image alteration.

We have chosen the first solution for two reasons :

- It is difficult to know the real sensitivity to noise or to image alteration of a motion estimator.
- In a high resolution image sequence, motion induces large displacements, up to 200 or 300 pixels. One of the best solutions to quickly estimate such motions is to use a hierarchical structure (image pyramid) [2], [3]. The filtering process is then included in the creation of this hierarchical structure.

Having organized image information in a hierarchical manner, a recursive block matching technique is used to estimate the optical flow [5], [10].

### 3.1. Hierarchical structure

The basic idea is to create a pyramidal representation of an image [1] using the following algorithm :

$$\begin{aligned} & \text{if } (x \bmod 2 = 0) \text{ and } (y \bmod 2 = 0) \\ & \text{then } I^{l+1}(x/2, y/2, t) = f * I^l(x, y, t) \end{aligned}$$

where  $*$  denotes the convolution operator and  $f$  is a given filter.  $I^l$  is interpreted as a family of images, where  $l$  indicates the level of resolution (or scale). The larger  $l$ , the more blurred the original image  $I$  is, finally showing the larger structures in the image.

Our hierarchical image structure is built using a low-pass filtering such that film grain and deteriorations disappear at higher levels of the pyramid. Indeed, such high spatial frequencies disturb the motion estimation process.

### 3.2. Hierarchical motion estimation

Our method combines the principle of hierarchical motion estimation with a block matching algorithm.

In first step, the global motion is estimated allowing only a coarse velocity field to result and, in lower hierarchical levels, the details of the vector field are calculated as relatively small update around the estimated vector resulting from the previous higher level.

At each level, displacements are estimated using a recursive block matching algorithm [10]. For each pixel of the current grid, we search for the displacement vector which yields the minimum value of a common criterion based on the so-called displaced frame difference (DFD) :

$$E(\underline{p}, \underline{d}, t) = \sum_{\underline{p}' \in W_{\underline{p}}} (DFD(\underline{p}', \underline{d}, t))^2$$

with  $DFD(\underline{p}', \underline{d}, t) = I(\underline{p}', t) - I(\underline{p}' - \underline{d}, t - dt)$  representing a neighbouring window of  $n \times n$  pixels centered at pixel  $\underline{p}'$ , and  $\underline{d}$  the displacement of  $\underline{p}$  from time  $t$  to  $t - dt$ .

More formally, this recursive search consists of the following steps :

First, the estimated displacement from the higher level is used as the prediction of the present location :

$$\underline{d}_0^l(\underline{p}) = \underline{d}^{l+1}(\underline{p}) \times 2$$

To economize the calculational effort, rather than doing full block matching search, we check only 5 vectors (around the predicted position) in the first step and at the very most 3 vectors in the following steps. Figure 3 illustrates this procedure.

Then, our algorithm selects the best displacement candidate

$$\underline{\delta}_1^l, \underline{\delta}_1^l \in \{(0,0), (-1,0), (1,0), (0,1), (0,-1)\} \text{ according to criterion } E(\underline{p} + \underline{d}_0^l(\underline{p}) + \underline{\delta}_1^l, t).$$

The current displacement is then updated :  $\underline{d}_1^l = \underline{d}_0^l + \underline{\delta}_1^l$

In the next search steps, 3 new candidates are evaluated. Their position depends on the best previous candidate :

$$\begin{aligned} \underline{\delta}_{i-1}^l = (1,0) &\Rightarrow \underline{\delta}_i^l \in \{(0,0), (1,0), (0,1), (0,-1)\} \\ \underline{\delta}_{i-1}^l = (-1,0) &\Rightarrow \underline{\delta}_i^l \in \{(0,0), (-1,0), (0,1), (0,-1)\} \\ \underline{\delta}_{i-1}^l = (0,-1) &\Rightarrow \underline{\delta}_i^l \in \{(0,0), (1,0), (-1,0), (0,1)\} \\ \underline{\delta}_{i-1}^l = (0,1) &\Rightarrow \underline{\delta}_i^l \in \{(0,0), (1,0), (-1,0), (0,-1)\} \end{aligned}$$

where  $i$  denotes the search iteration number, and displacement  $(0,0)$  is related to the best previous selected candidate. Notice that the candidates that have already been checked do not need further evaluation.

The current displacement is then updated with the best candidate :  $\underline{d}_i^l = \underline{d}_{i-1}^l + \underline{\delta}_i^l$

The updating process is stopped at the moment the update falls under a threshold, or in case the previous selected candidate remains the best (local minimum), or after a fixed number of iterations.

Finally, we design an adaptive search strategy preventing that all possible vectors need to be checked and thus providing fast block matching search. For a maximum displacement magnitude of  $\pm 3$  pixels, this method checks only 20 candidates, while an exhaustive method checks 49. So, the processing speed increases by almost a factor 2.5.

### 3.3. Detection of local deteriorations

Once the optical motion flow is correctly estimated, the next frame could be rebuilt without any deteriorations. The absolute value of the DFD is considered as a measure of the quality of the estimated motion. Outliers, usually corresponding to deteriorations, occlusions or disocclusions, are detected when this criterion is higher than a threshold  $S$ . These outliers are potential deteriorations.

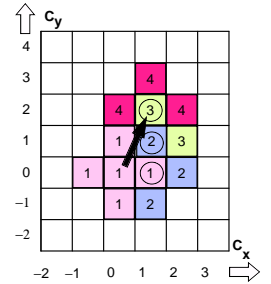


Figure 3 : Adaptive block matching search

To deal with occlusions and disocclusions, we use a third image in our estimation scheme. The same process as described above is performed between the image at time  $t$  and the image at time  $t+dt$ . **Common** spurious points from the two independent motion estimation and comparison processes are selected as deteriorations (fig. 4).

#### 4. Combination of the two previous detectors

A very good detection rate can be achieved by combining the morphological and the dynamic detectors. The main problems of the latter detectors - false detections and threshold tuning - are bypassed with the double evidence provided by "ANDing" the results of the two detectors. Therefore, the thresholds are fixed at low values in order to detect every deteriorated pixel, but this also increases the number of wrong detections. However, these are not the same for the first and the second detector, and the double evidence eliminates them.

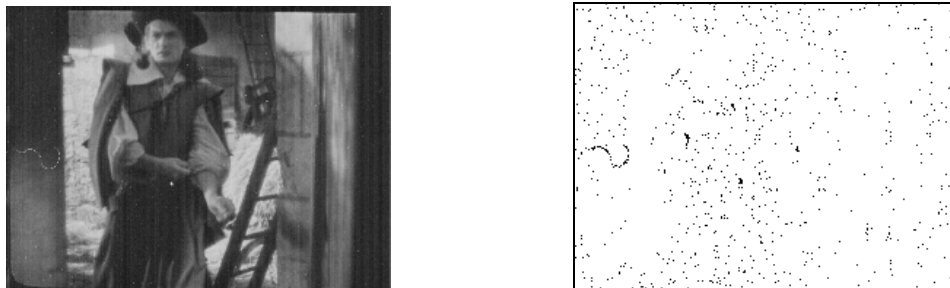


Figure 4 : Frame  $l(t)$  of a film sequence (La belle et la bête, 1946), and defects detection on  $l(t)$

#### 5. Summary and Conclusions

We have presented an efficient detector of local deteriorations of old films. This detector combines two different detectors: a morphological detector and a dynamic one. Using a usual criterion in the motion estimation step, we obtain a rate of 3 % of false detections and 5 % of undetected deteriorations. Defects detection is achieved in about 230 sec. per 2200 x 1640 frame on a standard workstation: 15 sec. for the morphological detection and about 215 sec. for the dynamic detection (which uses 3 images) in an early unoptimized version.

Future work will concern detection of oversized defects, intensity distortions, image unstability and, of course optimization, eventually parallelization, of our algorithms.

#### 6. Acknowledgements

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#### 7. References

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