Diagnosis and Treatment of Film Tear in Degraded Archived Media*

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Abstract

A common form of degradation in archived film is film tear. This is caused by the physical ripping of the film. Tear causes displacement of a region of the degraded frame and the loss of image data. As of yet no method of automatically treating film tear has been proposed. This paper outlines an algorithm to automatically detect and restore torn frames. Tear Detection is facilitated by the presence of a large edge feature, unlikely to be caused by other forms of degradation, in the torn frame. Restoration is achieved by estimating the regional displacement and recovering missing image data.

1 Introduction

Recent years have seen the availability of digital media increase dramatically. The extra broadcast channels available have increased the demand for archived film and video. However the quality of archived material often does not match the high standards of quality demanded by digital media due to degradation of the film. The most common forms of degradation include intensity fluctuations in the film (known as flicker [4]) and presence of dirt and sparkle (also called blotches [3]) on the film. Another common form of film degradation is film tear which is caused by the physical ripping of the film. Like blotches, tear results in missing image data but additionally causes displacement in a region of the frame. Figure 1 indicates the physical displacement and the large edge feature caused by the tear. Up until now tear was treated by manually highlighting the displaced region and then copying and pasting the region until the edges were properly aligned. This paper outlines a method to automate this process. The tear is diagnosed by detecting the edge feature and then using the edge and motion information [2] to delineate the Tear. Treatment is performed by estimating the global motion separately for the regions either side of the tear and deciding which global motion corresponds to tear.

2 Tear Diagnosis

Tear Diagnosis is broken into two separate problems of *detecting* torn frames and *delineating* the tear within a detected frame (marking the location of the tear on the frame). This from our experience increases the speed of diagnosis by performing a quick high level scan to detect torn frames and then performing the intensive delineation processes on suspected frames only.

Torn frames are detected by looking for the presence of a large edge feature in a frame. Large Edge features are characterised by high gradient magnitudes and are found by calculating the skew, S, of a histogram of gradient magnitudes for each frame where the skew for frame n, S_n is given by

$$S_n = \frac{G_n^{99}}{\mu_n^g} \tag{1}$$

where μ_n^g is the mean gradient magnitude and G_n^{99} is the gradient magnitude bounding the top 1% of area of the histogram. A torn frame will result in a Skew measurement that is higher than that for the surrounding frames (See Fig 5).

Torn frames are isolated by imposing a gaussian model on the skew measurements and selecting measurements three standard deviations above the mean. This is then repeated omitting previously detected frames. Shifts in the mean caused by shot cuts are eliminated by subtracting the output of a five tap median filter from the skew measurements. Figure 5 shows the measurements for two corrupted sequences. Because of the lack of real footage available a sequence of 20 frames was artificially corrupted with 5 tears. Due to the large concentration of tears in this sequence not all tears were detected even after the second pass despite the presence of well defined peaks in the skew measurements.

*This work was funded by a grant from IRCSET Ireland.
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Proceedings of the 17th International Conference on Pattern Recognition (ICPR'04)
1051-4651/04 $ 20.00 IEEE

2.1 Tear Delineation

The problem is to construct a binary field, b, where

$$b(\mathbf{x}) = \begin{cases} 1 & \text{the pixel } \mathbf{x} \text{ is a tear site} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The field b is constructed by using the value of $b(\mathbf{x})$ that maximises the probability $P(b(\mathbf{x}))|G, \Delta_f, \Delta_b, B)$ where G is a field of Gradient magnitudes for the frame, where B is the approximation to the tear and where Δ_f and Δ_b are the forward and backward Displaced Frame Differentials (DFDs) respectively. The DFDs are given by

$$\begin{aligned} \Delta_f(\mathbf{x}) &= I_n(\mathbf{x}) - I_{n+1}(\mathbf{x} + \mathbf{d_{n,n+1}}(\mathbf{x})) \\ \Delta_b(\mathbf{x}) &= I_n(\mathbf{x}) - I_{n-1}(\mathbf{x} + \mathbf{d_{n,n-1}}(\mathbf{x})) \end{aligned} \tag{3}$$

where I_k is the k^{th} frame and where $d_{k,l}$ is the motion vector between frames k and l. According to Bayes Law the posterior can be expressed as

$$\begin{aligned} P(b(\mathbf{x})|G, \Delta_f, \Delta_b, B) \;\propto & \; P_l(G, \Delta_f, \Delta_b|B, b(\mathbf{x})) \\ & \times P_s(b(\mathbf{x})|B) \end{aligned} \tag{4}$$

where P_l is the data likelihood and P_s is a spatial prior which applies a spatial smoothness constraint.

The **Data Likelihood** tries to match the constraint that at tear sites the forward and backward DFDs and the gradient magnitude are large. It also tries to match the constraint that the sign of DFDs are the same. The expression used to calculate the likelihood, $P_l(G, \Delta_f, \Delta_b|B, b)$, is

$$\begin{aligned} & P_l(\Delta_f(\mathbf{x}), \Delta_b(\mathbf{x}), G(\mathbf{x})|b(\mathbf{x}), B(\mathbf{x})) \propto \\ & \exp\Bigg\{ -\Big(1 - b(\mathbf{x})\Big) \Bigg[\Lambda_0 \left(\frac{\Delta_f(\mathbf{x})^2}{2\sigma_f^2} + \frac{\Delta_b(\mathbf{x})^2}{2\sigma_b^2} + \frac{G(\mathbf{x})^2}{2\sigma_g^2} \right) \\ & + \Lambda_s \Big(1 + \mathrm{sign}\Big(\Delta_f(\mathbf{x})\, \Delta_b(\mathbf{x})\Big)\Big) \Bigg] - \alpha\, b(\mathbf{x}) \Bigg\} \end{aligned} \tag{5}$$

where the DFDs, Δ_b and Δ_f, and the gradient, G, are normalised by their variances, σ_b, σ_f and σ_g respectively; where Λ_0 and Λ_s are equation parameters and where α is the energy for $b(\mathbf{x}) = 1$. In this case α is a constant and effectively acts as a threshold or as an energy penalty for $b(\mathbf{x}) = 1$. Values of $\Lambda_0 = 1$ and $\Lambda_s = 0.5$ are typical for all the tested sequences. A typical value of α is 10 and this comprises of a value of 3 to compensate for the energy of each of the DFDs and the gradient (9 in total) and 1 to compensate for the energy due to the sign of the DFDs.

The **Prior** $P_s(b|B)$ encourages spatial smoothness in the result. A Gibbs Energy Prior is adopted and is given by the following expression

$$P_s(b(\mathbf{x})|B(\mathbf{x})) \;\propto\; \exp\left(-\Lambda_b \sum_{\mathbf{u} \in S_N(\mathbf{x})} \Big| b(\mathbf{x}) - b(\mathbf{u}) \Big| \right) \tag{6}$$

where $S_N(\mathbf{x})$ is the 8 connected neighbourhood of $\mathbf{x}$. A value of 1 is used for the parameter Λ_b.

The **Optimised Solution** is obtained using the Iterated Conditional Modes algorithm [1]. The state of each pixel $\mathbf{x}$ is given by the value of $b(\mathbf{x})$ that maximises the posterior $P(b(\mathbf{x})|G, \Delta_f, \Delta_b, B)$. Iteration is continued until there is no change in successive estimates. Typically convergence is exponential and occurs within ten iterations. The process is initialised by using a blotch detector to generate an estimate of the result. The Blotch detector used is based on the SDI detector [3] [6]. The motion of objects is tracked forwards and backwards through a sequence using motion estimation techniques [2] [3]. Since a tear is not present on consecutive frames it will not be matched by the estimator and will result in large forward and backward DFDs, Δ_f and Δ_b, at tear sites and the sign of the DFDs will be the same. The SDI detector is defined by the expression

$$B(\mathbf{x}) = \begin{cases} 1 & |\Delta_f| > \delta_t,\ |\Delta_b| > \delta_t,\ \Delta_b, \Delta_f > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where $B(\mathbf{x}) = 1$ implies that the pixel $\mathbf{x}$ is a tear site and δ_t is a threshold applied to the DFDs. Figure 6 shows the results for the SDI detector and the final outcome.

3 Tear Treatment

Having delineated the tear the torn frame can be restored. Tear causes displacement in a region of the torn frame. In order to estimate the displacement it is necessary to calculate the global motion of the region. Figure 3 shows the vector field for four consecutive frames where the second image is of a torn frame. The distribution of the field on the torn frame differs significantly on either side of the tear and the magnitude of the vectors in the displaced bottom region are significantly larger. The displacement is calculated by dividing the frame into two regions either side of the tear and by calculating the modes of vector histograms of both regions (Figure 4 shows a contour map of the histograms for the two regions of a torn frame). The mode is an estimate of the global motion of the region. One of the two regions must be selected as the displaced region. Two observations can be made. The first is that displacement caused by tear is likely to be larger than displacement caused by other factors. The second is that motion of the displaced region is more coherent and hence the vectors are more concentrated about the mode of the histogram (See Figure 1). The ratio of histogram entropy to motion vector mean is used as it factors both observations in the decision. The region with the lower ratio is chosen.

A bin size of $1/8$ pel is used for the vector histograms. Vectors are also weighted according to their accuracy. The expression for the weight of a vector at pixel $\mathbf{x}$, $w(\mathbf{x})$ is given by

$$w(\mathbf{x}) = \left\|\mathbf{G}(\mathbf{x})\right\| \left|\cos\Big(\angle\big(\mathbf{G}(\mathbf{x})\big) - \angle\big(\mathbf{d_{n,n-1}}(\mathbf{x})\big)\Big)\right| \quad (8)$$

This gives high weights to vectors where the gradient magnitude is large and where the gradient and motion vectors have similar phases.

The restored image, I_r, is calculated using the following expression

$$I_r(\mathbf{x}) = r'(\mathbf{x})I_d(\mathbf{x}) + r(\mathbf{x})I_d(\mathbf{x} + \mathbf{D_t}) \quad (9)$$

where $\mathbf{D_t}$ is the calculated regional displacement; where I_d is the corrupted frame , where $r(\mathbf{x})$ is a binary field where a value of 1 indicates that the pixel $\mathbf{x}$ is in the displaced region of the frame and where $r'(\mathbf{x})$ is the compliment of $r(\mathbf{x})$. Bilinear interpolation is used to retrieve image data from non-integer pixel sites.

Figure 2 shows a close up of a frame which has been restored. A blotch remover [3] could be used to recover missing data from the frame. As no satisfactory method of dividing the frame into two regions was developed a picture editor was used to do this manually.

4 Final Comments

This paper introduces an original method of automatically treating film tear. The use of motion vector histograms is crucial as it allows the displacement caused by tear to be estimated and removed. The displacement is accurately estimated and can be seen by the alignment of edges that cross the tear. Using a blotch removal process will remove the edge feature from the frame and fully remove the effects of the tear. The Diagnosis algorithm accurately detects torn frames and the accuracy of the process will improve with longer sequences as the relative frequency of occurrence of torn frames decreases. Improving the results for delineation and the treatment of rotational displacement are the main areas of further study.

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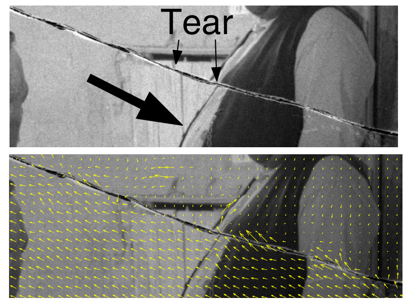

Figure 1. The arrows in the top image indicate the displacement caused by the tear. The bottom image shows the vector field for the frame. The vectors indicate the relative position of the previous frame to the current frame.

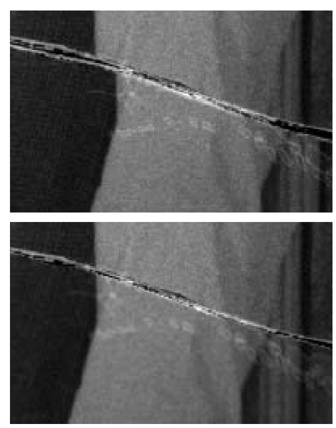

Figure 2. Top image is a zoom of the torn frame; The Bottom is a zoom of the treated frame.

Figure 3. Motion vector fields for four consecutive frames. The second image shows the torn frame. In the third image there is an apparent regional displacement present but this is solely a consequence of the tear.

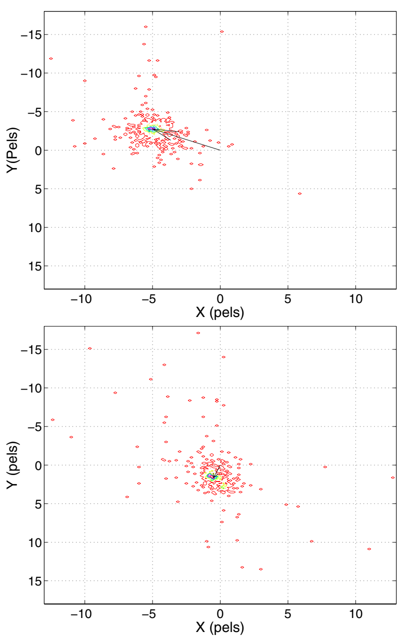

Figure 4. Contour maps of the vector histograms for the two regions of the torn frame. The arrow points from the origin to the mode of the histogram.

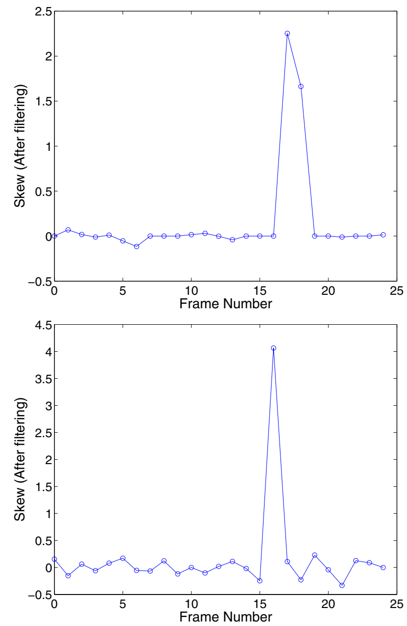

Figure 5. Graphs show a plot of the skew values against frame numbers for two separate test sequences. There are 2 tears on consecutive frames in the first sequence and a single tear in the second.

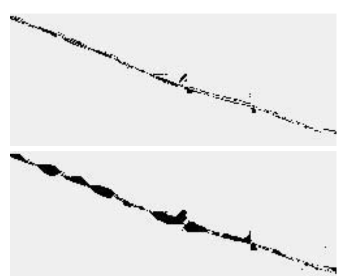

Figure 6. Results of the Tear Delineation Process on the frame shown in Figure 1. The top map shows the results after the SDI detector and the bottom shows final result of the delineation process.