FLICKER COMPENSATION FOR ARCHIVED FILM USING A MIXED SEGMENTATION/BLOCK-BASED NONLINEAR MODEL

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ABSTRACT

A new nonlinear method for the compensation of temporal brightness variations (commonly referred to as flicker) in archived film sequences is presented. The proposed method is motivated by fundamental principles of photographic image registration and provides a substantial level of adaptation to temporal but also spatial variations of picture brightness. Our approach is driven by segmentation of input frames to regions of homogeneous brightness which are used to provide reliable measurements of flicker parameters. Additionally our scheme provides an efficient mechanism of temporal filtering which makes it suitable for the compensation of long duration film sequences while it addresses problems arising from scene motion using a motion-compensated greylevel tracing approach. We present experimental evidence which suggests that our method offers high levels of performance and compares favourably with competing state-of-the-art techniques.

1. INTRODUCTION

Flicker refers to random fluctuations of image brightness which is a signature impairment in archived films. While film ageing, multiple copying, mould and dust may also be contributing factors, the main underlying cause is inconsistent film exposure at the acquisition stage. Flicker has often been categorised as a global artefact in the sense that it affects frames in their entirety as opposed to so-called local artefacts such as dirt, dust, or scratches which affect a limited number of frames and are usually localised on the image plane. However flicker may also contain an element of spatial variation within the boundaries of a single frame. While there are instances where the profile of this spatial variation can remain virtually unchanged from one frame to the next, it is also not uncommon for it to change in an unpredictable manner. This renders any attempt at precise modelling a difficult task. Contributing causes can be traced to incorrect light synchronisation, fogging, vignetting, mould static marks caused by mechanical friction of the film strip and so on.

Initial efforts on flicker modelling reported in the literature assumed that the entire degraded frame was affected in a near-uniform fashion. In [1] flicker was modelled as a global intensity shift between a degraded frame and the mean level of the shot to which this frame belongs. In [2] flicker was expressed as a multiplicative constant relating the mean level of a degraded frame to that of a reference frame.

Spatial variation was considered in [3, 4] where additive or multiplicative constants were replaced by 2nd order polynomial approximations. Work in [5] approached the problem using histogram equalisation. In [6] a nonlinear method derived from the Huyter-Driffield $D(\log E)$ characteristic is proposed. Correction values are computed independently for each greylevels, and a polynomial compensation profile is created afterwards. In [7] joint Probability Density Functions (pdfs) are estimated locally at several control points and a dense compensation function is obtained using interpolation splines. In [3] a robust hierarchical framework was proposed to estimate the polynomial functions, going from zero-order to 2nd order polynomial. In [8] estimation of semi-global parameters was performed based on a block-partitioning of the degraded frame. Bilinear interpolation was used to obtain a dense parameter field. A nonlinear spatially-adaptive version of the work detailed in [6] is presented in [9]. Nonlinear flickers compensation profiles are estimated on a block-based basis between motion-compensated frames and the spatial adaptation is performed through bilinear interpolation of the compensation values.

While the above efforts addressed the fundamental problem with varying degrees of success far fewer attempts were made to formulate a complete and integrated compensation framework suitable for the challenges posed by processing longer sequences. In [5] references frames were appointed within a sequence of frames and a linear combination of the inverse histogram equalisation functions of the two closest reference frames (forward / backward) was used for compensation purposes. In [8] compensation was performed recursively. Error propagation is likely in this framework as previously generated compensations are used to estimate future flicker parameters. A bias is introduced as the restored frame is a mixture of the actual compensated frame and the original degraded one. In [4] an approach motivated from video stabilisation described in [2] is proposed. Several flicker parameter estimations are computed for a degraded frame within a temporal window and a filter is employed to provide a degree of smoothing of those parameters.

This paper is organised as follows. Section 2 provides a brief review of flicker nonlinear modelling while Section 3 explains how the spatial adaptation is achieved in a block-based approach coupled with segmentation information. The temporal compensation framework is detailed in Section 4 while experimental results are presented in Section 5 and conclusions are drawn in Section 6.
2. NONLINEAR MODELLING

As described in [6], the Density versus log Exposure characteristic \( D(\log E) \) attributed to Hurter and Driffield [10] (solid line in Figure 1) can be used to characterise exposure inconsistencies and their corresponding density errors (dashed line). The relationship between \( \log(\text{Exposure}) \) and Density is nonlinear and as a consequence density errors may vary for a constant amount of exposure error. The amount of compensation \( \Delta t \) required for an observed greylevel \( I_t \) in frame \( F_t \) is calculated relative to a corresponding observed greylevel \( I_{\text{ref}} \) in reference frame \( F_{\text{ref}} \) (assumed to be flicker-free) as \( h_t = \frac{I_t - \Delta t}{I_{\text{ref}}} \). A greyscale compensation profile \( P_t \) (dashed curve in Figure 2) between a degraded frame and a reference frame (typically the first one of the sequence) is then estimated as a least-squares quadratic polynomial fit to raw compensation measurements \( \Delta t_{\text{ref}} \) (solid line). In this example, the shape of the profile suggests that the compensation to be applied is unimodal, peaking towards the middle of the greyscale as well as concave which is in agreement to the Brightness characteristic. As described in [6], the Density versus log Exposure characteristic is used to estimate compensations and vice versa. A weighted polynomial fitting based on reliability measurement \( r_{\text{ref}}(h) \) defined by greylevels frequency of occurrence is used. An example of such a reliability distribution is shown at the bottom of Figure 2 while the modified compensation profile \( C_{\text{ref}} \) due to weighting is shown as a solid, lighter-shade line. A comparison with the original unweighted profile \( P_{\text{ref}} \) (dashed line) confirms that more densely populated greylevels have a stronger influence on the fidelity of the fitted profile with respect to the raw compensation data.

In addition, motion estimation and compensation is performed in [9] to cope with real movie sequences. The Black and Anandan dense motion estimator ([11]) is used as it is well equipped to deal with violations of the brightness constancy assumption. The motion predictor error is a key indicator when it comes to intensity error profile estimation as it is employed to decrease the influence of incorrectly motion compensated pixels.

3. SPATIAL ADAPTATION

Spatial adaptation is achieved by means of block-based frame partitioning and is illustrated in Figure 3. Correction profiles \( C_{\text{ref},b} \) are estimated directly on each block \( b \) of frame \( F_t \) yielding values for \( \Delta t_{\text{ref},b} \) and \( P_{\text{ref},b} \). It will be explained in the next section how segmentation information can improve the compensation profile estimation. For the moment, we perform estimation on entire blocks. As brute force compensation of each block would lead to blocking artefacts at block boundaries, a weighted bilinear interpolation is used based on the inverse of the Euclidean distance \( d_b(\bar{p}) \) of the considered located in \( \bar{p} \) to the center of each blocks. In addition, reliability measurements \( r_{\text{R,B}} \) of \( C_{\text{R,B}} \) detailed in Section 4.1 are used as a second weight in the bilinear interpolation. Intensity error estimation \( C_{\text{I,B}} \) are finally weighted by the normalised product of the two previous terms \( \sum_{b=1}^{N} d_b(\bar{p}) \cdot r_{\text{R,B}}(F_t(\bar{p})) \cdot r_{\text{I,B}}(F_t(\bar{p})) \). The compensation value is given by:

\[
F'_t(\bar{p}) = F_t(\bar{p}) - \sum_{h=1}^{N} d_b(\bar{p}) \cdot r_{\text{R,B}}(F_t(\bar{p})) \cdot C_{\text{I,B}}(F_t(\bar{p}))
\]

3.1 Segmentation-based compensation profile estimation

So far the entire block has been considered for the compensation profile estimation. The weighted polynomial fitting and the motion prediction error allow to deal with outliers. In our approach we divide a degraded block into regions of uniform intensity and then perform compensation profile estimations for such regions. Afterwards, the multiple profiles are combined to create a compound compensation profile. An unsupervised segmentation algorithm called JSeg [12] is
Figure 3: Segmentation and block partitioning using a $3 \times 3$ grid of the 20th frame of the sequence tunnel. The processed pixel and the centre of each blocks are represented by black and white dots respectively. The black lines represent the distances $d_{k}(\beta)$ while the white lines show the regions boundaries.

used to partition the degraded image $F_t$ into uniform regions (Figure 3). The segmentation map is then overlaid onto the block grid, generating block-based sub-regions $F_{t,n}^{b}, b$ being the index of the region within the block $b$. Local compensation profiles $C_{t,ref\,b}^{k}$ and associated reliabilities $r_{t,ref\,b}^{k}$ are then computed independently on each sub-region of each block.

Finally the block compensation value associated to greylevel $I_i$ for block $b$ is obtained by maximising the reliability of the segmentation-based estimations:

$$C_{t,\text{ref},b}(I_i) = \max_k \{C_{t,\text{ref},b}(I_i)\}$$

and

$$r_{t,\text{ref},b}(I_i) = \max_k \{r_{t,\text{ref},b}(I_i)\}$$

(2)

4. FLICKER COMPENSATION FRAMEWORK

Several compensation schemes allowed the compensation of the degraded frame according to a fixed reference frame $F_{t,ref}$. This framework only permits to restore static sequences as performance deteriorates with progressively longer temporal distances between a compensated frame and the appointed reference especially when considerable levels of camera and scene motion are present.

Let us denote $I_R$ a flicker-free greylevel mapped to flicker-contaminated greylevel $I_i$. $I_R$ can be obtained by averaging the neighbouring greylevels $I_j$ within a sequence, using the relation $I_R = I_R - \Delta I_R(I_i)$ (see Section 2):

$$\frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} I_i = \frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} (I_R - \Delta I_R(I_i)) = I_R - \frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} \Delta I_R(I_i)$$

(3)

$N$ being, in general, a number of frames specifying a temporal sliding window centred at the current frame so that a degree of dynamic adaptation to localised content is achieved. Considering the weak and intuitively plausible assumption that exposure errors $\Delta I_R(I_i), i \in [t - N/2; t + N/2]$ are zero-mean distributed we obtain:

$$\lim_{N \to \infty} \frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} \Delta I_R(I_i) = 0 \Rightarrow \lim_{N \to \infty} \frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} I_i = I_R$$

(4)

The previous equation simply states that the average of greylevels $I_i$ mapped to greylevel $I_R$ within a temporal window centred at frame $t$ yield an estimate of flicker-free greylevel $I_R$. This assumption is used in the compensation profile estimation scheme in the following section.

4.1 Dynamic estimation of the intensity error profile

The sliding window concept developed previously will now extend to the intensity error profile estimation. The intensity error $\Delta I_R(I_i)$ between $I_R$ and $I_i$ is estimated by first considering the raw compensation profile:

$$\Delta I_R(I_i) = I_R - I_i \approx \frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} I_i - I_i$$

$$\approx \frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} (\Delta I_R(I_i) + I_i) = I_R - \frac{1}{N} \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} \Delta I_R(I_i)$$

(5)

(6)

Subsequently we use the polynomial approximation $C_{t,R}(I_i) \approx \Delta I_R(I_i)$ which enhances the robustness of the intensity error estimation (Section 2) to obtain a more reliable estimation. In other words a compensation value $C_{t,R}(I_i)$ on the profile is obtained by averaging compensation values $C_{t,R}(I_i)$ where $i \in [t - N/2; t + N/2]$ i.e. a sliding window of width $N$ centred at the current frame as illustrated in Figure 4.

In this figure the compensation and reliability curves are simplified versions of the curves in Figure 2. We incorporate reliability weighting (see Section 2) by taking into account individual reliability contributions for each frame within the sliding window and normalising for unity:

$$C_{t,R}(I_i) = \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} r_{t,i}(I_i) \cdot C_{t,i}(I_i)$$

and

$$\sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} r_{t,i}(I_i) = 1$$

(7)

Thus a reliable compensation value $C_{t,R}(I_i)$ will have a proportional contribution to the computation of $C_{t,R}(I_i)$. In addition a reliability measurement for $C_{t,R}(I_i)$ is obtained by summing unnormalised reliabilities $r_{t,i}(I_i)$ of interframe compensation values $C_{t,i}(I_i)$ over the sliding window, which will be a useful information in the spatial adaptation of the algorithm:

$$r_{t,R}(I_i) = \sum_{i=t-\frac{N}{2}}^{t+\frac{N}{2}} r_{t,i}(I_i)$$

(8)

4.2 Intensity error estimation between distant frames using motion compensated greylevel tracing

As Frames $F_t$ and $F_r$ are usually distant in the video stream, large motion may be present and the motion compensation...
framework referred to in Section 2 cannot be used directly. Nevertheless it is still sensible to carry out intensity error profiles between motion-compensated consecutive frames and to combine them afterwards. Raw compensation profiles and associated reliabilities are computed between consecutive frames in both directions yielding values \( \Delta I_{t+1,i} \) and \( r_{t+1,i} \) for \( t = [0:L] \), \( L \) being the number of frames of the sequence. The mapping functions are then combined as follows:

\[
\Delta I_{t+1,i} = \Delta I_{t+1,i} + \Delta I_{t+1,i} + \Delta I_{t+1,i} (l + \Delta I_{t+1,i})
\]  

(9)

which can be generalised for \( \Delta I_{t+1,i} > 2 \). This amounts to tracing compensation values from one frame to the next under the influence of motion. The associated reliability is computed as:

\[
r_{t+1,i} = \min(r_{t+1,i}, r_{t+1,i} + \Delta I_{t+1,i} (l + \Delta I_{t+1,i}))
\]  

(10)

The above also generalises for any frame-pair. If a specific compensation \( \Delta I_{t+1,i} \) is unreliable then the min operator above ensures that this also renders the compensation reliability \( r_{t+1,i} \) weak.

5. EXPERIMENTAL RESULTS

The proposed flicker compensation framework is compared with two spatially-adaptive state-of-the-art techniques, detailed respectively in [8] and [7]. Four test sequences Boat, Lumière, Tunnel and GreatWall composed of 93, 198, 50 and 141 frames respectively are used for evaluation purposes. The first three sequences contain slight unsteadiness but substantial flicker. The impairments are highly nonlinear and presents a various degrees of spatial variability. The motion content is quite low as the camera is fixed. The last sequence panoramic pan of the Chinese Great Wall.

Flicker reduction algorithms are traditionally evaluated by examining the variation of the mean frame intensity over time. This measurement fails to address the spatial variation issue thus two new visualisation tools are proposed in order to highlight the differences which occurs within the frames of the sequences themselves. They estimate the similarity between consecutive motion and flicker-compensated frames which should very similar, any differences being only due to motion estimation inaccuracy. We further employ the following two measures:

\[\text{measure}_1: \text{Mean absolute difference between co-sited pixels of the frames. Each pixel's influence is weighted by the corresponding motion prediction error. The better the compensation, the closer to zero this value should be.}\]

\[\text{measure}_2: \text{A threshold in the available greyscale (typically between 0 and 255) is employed. The percentage of co-sited pixels having an absolute difference lower than this threshold is counted. Each pixel's influence is weighted by the motion prediction error. A curve for the entire greyscale is then computed by varying the threshold as necessary. The higher the percentage the better the performance of the scheme under assessment.}\]

The above measurements are extended to image sequences by accumulating the measurements between consecutive frames. Normalising the values by the running total number of frames gives more clarity to the plots, which are respectively presented in Figures 5 and 6. Overall, our results show that our algorithm performs well in both in terms of measured performances as well as subjective quality. It can be observed that the proposed technique compares favourably for all test sequences.

6. CONCLUSION

In this paper, a new scheme for flicker compensation was introduced. The approach was based on nonlinear modelling introduced in previous work but contains important new components that allow it to address successfully the challenges posed by spatial variability of flicker impairment, appointment of reference frames and scene motion. Our results demonstrate that the algorithm is very effective towards flicker compensation both in subjective and objective terms and compares favourably to state-of-art methods that feature in the literature.

REFERENCES


Figure 5: Time-normalised cumulative average of the absolute difference between consecutive motion-compensated frames for the available test sequences (measure_1)

Figure 6: Percentage of motion-compensated pixels having an absolute difference inferior to a variable threshold for the available test sequence (measure_2)