Correction of Intensity Flicker in Old Film Sequences

P. M. B. van Roosmalen, R. L. Lagendijk, and J. Biemond

Abstract—Temporal intensity flicker is a common artifact in old film sequences. Removing disturbing temporal fluctuations in image intensities is desirable because it increases both the subjective quality and, where image sequences are stored in a compressed format, the coding efficiency. We describe a robust technique that corrects intensity flicker automatically by equalizing local frame means and variances in the temporal sense. The low complexity of our method makes it suitable for hardware implementation. We tested the proposed method on sequences with artificially added intensity flicker and on original film material. The results show a great improvement.

Index Terms—Filtering, image analysis, image restoration, parameter estimation.

I. INTRODUCTION

NIQUE records of historic, artistic, and cultural developments of every aspect of the twentieth century are stored in huge stocks of archived moving pictures. Many of these historically significant items are in a fragile state and are in desperate need of conservation and restoration. Restoration improves the subjective quality of the film sequences. It also leads to higher quality at identical bit rates when sequences are archived on new digital media with, for instance, the MPEG compression standard. This is because removing artifacts leads to smaller prediction errors. Although the original physical film may contain information useful to the restoration process, we confine ourselves to the digital domain. Digital image sequences are obtained by digitizing the output of the filmto-video telecine. It must be kept in mind that the earlier telecines have their limitations in terms of noise characteristics and resolution. Sometimes a copy on video obtained from an earlier telecine is all that remains of a film.

In recent years, several authors have proposed methods for correcting artifacts common to old film sequences such as noise reduction [1]–[5], line-scratch detection and removal [6], and blotch detection and removal [7], [8]. This paper deals with another common artifact, namely, intensity flicker in black-and-white film sequences. We define intensity flicker as unnatural temporal fluctuations in perceived image intensity that do not originate from the original scene. Intensity flicker has a great number of causes, e.g., aging of film, dust, chemical processing, copying, aliasing, and, in the case of earlier film cameras, variations in shutter time. Neither equalizing the intensity histograms nor equalizing the mean frame values of consecutive frames, as suggested in [9]–[11], form general solutions to the problem. These methods do not take changes

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in scene contents into account, and they do not appreciate the fact that intensity flicker can be a spatially localized effect. We propose equalizing local intensity means and variances in a temporal sense to reduce the undesirable temporal fluctuations in image intensities. The proposed method was developed to be implemented in hardware; therefore, the number of the operations per frame and the complexity of these operations have been kept as low as possible.

This paper is structured as follows. In Section II we model the effects of intensity flicker, and we derive a solution to this problem for stationary sequences. The reliability of the model parameters are analyzed. Section III extends the applicability of our method to include spatio-temporally nonstationary sequences by incorporating motion. In the presence of intensity flicker, it is difficult to compensate for motion of local objects in order to satisfy the requirement of stationarity. We therefore apply a method for compensating global motion (camera pan) and a method for detecting the remaining local object motion. Where local motion is detected, we refrain from estimating model parameters from the data but we interpolate these from model parameters estimated in stationary regions. Section IV shows the overall system of intensity-flicker correction and discusses some practical aspects. Experiments and results form the topics of Section V. Section VI concludes with a discussion.

II. ESTIMATING AND CORRECTING INTENSITY FLICKER IN STATIONARY SEQUENCES

We develop a method for correcting intensity flicker that is robust to the wide range of causes of this artifact. First, in Section II-A we model the effects of intensity flicker. We find a solution to this problem that is optimal in a *linear mean square error* sense. In Section II-B we concentrate on how the model parameters can be estimated for stationary image sequences, and we define a measure of reliability of those estimated parameters.

A. A Model for Intensity Flicker

It is not feasible to find explicit physical models for each of the mechanisms mentioned that cause intensity flicker. Instead, our model of the effects of this phenomenon is based on the observation that it causes temporal fluctuations in local intensity mean and variance. Since noise is unavoidable in the various phases of digital image formation, we also include a noise term in our model

$$Y(x, y, t) = \alpha(x, y, t) \cdot I(x, y, t) + \beta(x, y, t) + \eta(x, y, t).$$
(1)

Here x, y are discrete spatial coordinates and t indicates the frame number. Y(x, y, t) and I(x, y, y) indicate the observed

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and original image intensities. Note that by I(x, y, t) we do not necessarily mean the original scene intensities, but a signal that, prior to the introduction of intensity flicker, may already have been distorted. The distortion could be due to signal-dependent additive granular noise that is characteristic of film [12], for example. The multiplicative and additive intensity-flicker parameters are denoted by $\alpha(x, y, t)$ and $\beta(x, y, t)$. In the ideal case, when no intensity flicker is present, $\alpha(x, y, t) = 1$ and $\beta(x, y, t) = 0$ for all x, y, t. We assume that $\alpha(x, y, t)$ and $\beta(x, y, t)$ are spatially smooth functions.

The intensity-flicker-independent noise, denoted by $\eta(x, y, t)$, models noise that has been added to the signal after the introduction of intensity flicker. We assume that this noise term is uncorrelated with the original image intensities. We also assume that $\eta(x, y, t)$ is a zero-mean signal with known variance. Examples are quantization noise and thermal noise originating from electronic studio equipment (VCR, amplifiers, etc.).

To correct intensity flicker, we must first estimate the original intensity for each pixel from the observed intensities. We propose using the following linear estimator for estimating I(x, y, t)

$$\hat{I}(x, y, t) = \alpha(x, y, t)Y(x, y, t) + b(x, y, t).$$
(2)

If we define the error between the original image intensity and the estimated original image intensity as

$$\varepsilon(x, y, t) = I(x, y, t) - \hat{I}(x, y, t)$$
(3)

then we can easily determine that, given $\alpha(x, y, t)$ and $\beta(x, y, t)$, the optimal values for a(x, y, t) and b(x, y, t) in a *minimum mean square error* (MMSE) sense are given by

$$a(x, y, t) = \frac{\operatorname{var}[Y(x, y, t)] - \operatorname{var}[\eta(x, y, t)]}{\operatorname{var}[Y(x, y, t)]} \cdot \frac{1}{\alpha(x, y, t)}$$
(4)

$$b(x, y, t) = -\frac{\beta(x, y, t)}{\alpha(x, y, t)} + \frac{\operatorname{var}[\eta(x, y, t)]}{\operatorname{var}[Y(x, y, t)]} \cdot \frac{E[Y(x, y, t)]}{\alpha(x, y, t)}$$
(5)

where E[] stands for the expectation operator and var[] indicates the variance. It is interesting to note that from (2), (4), and (5), it follows that, in the absence of noise, $a(x, y, t) = 1/\alpha(x, y, t)$, $b(x, y, t) = -\beta(x, y, t)/\alpha(x, y, t)$, and $\hat{I}(x, y, t) = I(x, y, t)$. That is to say, the estimated intensities are exactly equal to the original intensities. In the extreme case that the observed signal variance equals the noise variance, we find that a(x, y, t) = 0 and $\hat{I}(x, y, t) = b(x, y, t) = E[I(x, y, t)]$; the estimated intensities equal the expected values of the original intensities.

B. Estimating Intensity-Flicker Parameters in Stationary Scenes

In the previous section we derived an LMMSE solution to intensity flicker, assuming that the intensity-flicker parameters $\alpha(x, y, t)$ and $\beta(x, y, t)$ are known. This is not the case in most practical situations, and these parameters will have to be estimated from the observed data. In this section, we determine how the intensity-flicker parameters can be estimated from stationary image sequences. We already assumed that $\alpha(x, y, t)$ and $\beta(x, y, t)$ are spatially smooth functions. For practical purposes, we now also assume that the intensity-flicker parameters are constant locally

$$\begin{cases} \alpha(x, y, t) = \alpha_{m, n}(t) \\ \beta(x, y, t) = \beta_{m, n}(t) \end{cases} \quad \forall x, y \in \Omega_{m, n}$$
(6)

where $\Omega_{m,n}$ indicates a small image region. The image regions $\Omega_{m,n}$ can, in principle, have any shape, but they are rectangular blocks in practice, and m, n indicate their horizontal and vertical spatial locations.

Taking both the expected value and the variance of Y(x, y, t) in a spatial sense for $x, y \in \Omega_{m,n}$ from (1) [keeping in mind the assumption that the zero-mean noise $\eta(x, y, t)$ is signal independent] and solving for the model parameters, we find for $x, y \in \Omega_{m,n}$

$$\beta_{m,n}(t) = E[Y(x, y, t)] - \alpha_{m,n}(t)E[I(x, y, t)]$$
(7)

$$\alpha_{m,n}(t) = \sqrt{\frac{\operatorname{var}[Y(x, y, t)] - \operatorname{var}[\eta(x, y, t)]}{\operatorname{var}[I(x, y, t)]}}.$$
(8)

To solve (7) and (8) in a practical situation, the mean and variance of Y(x, y, t) can be estimated directly from the regions $\Omega_{m,n}$ from the observed data. The noise variance was assumed to be known. Therefore, what remains to be estimated are the expected values and variances of I(x, y, t). In our work, we use for this purpose the frame corrected previously as a reference, for $x, y \in \Omega_{m,n}$

$$E[I(x, y, t)] \approx E[\hat{I}(x, y, t-1)] \tag{9}$$

$$\operatorname{var}[I(x, y, t)] \approx \operatorname{var}[\hat{I}(x, y, t-1)]. \tag{10}$$

There are some cases in which the $\hat{\alpha}_{m,n}(t)$ and $\hat{\beta}_{m,n}(t)$ are not very reliable. The first case is that of uniform image intensities. For any original image intensity in a uniform region, there are an infinite number of combinations of $\alpha(x, y, t)$ and $\beta(x, y, t)$ that lead to the same observed intensity. Another case in which $\hat{\alpha}_{m,n}(t)$ and $\hat{\beta}_{m,n}(t)$ are potentially unreliable is caused by the fact that (9) and (10) discard the noise in $\hat{I}(x, y, t)$ originating from $\eta(x, y, t)$. Considerable errors result in regions $\Omega_{m,n}$ in which the signal variance is small compared to the noise variance (low signal-to-noise ratio). It is clear from these examples that the accuracy of the estimated parameters decreases with decreasing signal variances. We now want a measure of reliability for $\hat{\alpha}_{m,n}(t)$ and $\hat{\beta}_{m,n}(t)$ to be able to avoid introducing significant errors in the corrected sequence. We define the measure of reliability, for $x, y \in$ $\Omega_{m,n}$

$$W_{m,n,t} = \begin{cases} 0 & \forall \operatorname{var}(Y(x, y, t)) < T_n \\ \sqrt{\frac{\operatorname{var}(Y(x, y, t)) - T_n}{T_n}} & \text{else} \end{cases}$$
(11)

where T_n is a threshold depending on the variance of $\eta(x, y, t)$. Large values for $W_{m,n,t}$ indicate reliable estimates; small values indicate unreliable estimates.

III. INCORPORATING MOTION

We have modeled the effects of intensity flicker, and we derived a solution for stationary sequences. Real sequences, of course, are seldom stationary. Equations (9) and (10) relate the mean and variance of the true (uncorrupted) frame t to the mean and variance of the frame corrected at t - 1. In the presence of motion, this relationship is not correct and leads to incorrect estimates of $\alpha(x, y, t)$ and $\beta(x, y, t)$ in (7) and (8). Visual artifacts result in the corrected sequence. Compensating $\hat{I}(x, y, t - 1)$ for motion would help satisfy the assumption of stationarity and would resolve the problem. This requires motion estimation.

Robust methods for estimating global motion (camera pan) based on phase correlation [13], [14] are relatively insensitive to fluctuations in image intensities. Unfortunately, the presence of intensity flicker hampers the estimation of local motion (motion in small image regions) because local motion estimators usually have a *constant luminance* constraint, e.g., pel-recursive methods and all motion estimators that make use of block matching in one stage or another [13]. Methods for estimating motion in sequences with illumination variations have been described in literature, though at the cost of relatively high complexity. Even if motion can be well compensated, a strategy is required for correcting flicker in previously occluded regions that have become uncovered.

For these reasons, our strategy for estimating the intensityflicker parameters in nonstationary scenes is based on compensating for camera pan followed by local motion detection. In regions containing local motion, the model parameters are interpolated. For estimating camera pan, we apply a method-based phase correlation [13], [14]. In the following, we describe our methods for local motion detection and for interpolation.

A. Detecting Local Motion

The underlying assumption of our local motion detector is that motion should only be detected if visible artifacts would be introduced otherwise. First, the observed image is subdivided into blocks $\Omega_{m,n}$ that overlap their neighbors both horizontally and vertically (Fig. 1). The overlapping boundary regions form sets of reference intensities. The intensity-flicker parameters are estimated for each block by (7) and (8) [using also (9) and (10)]. These parameters are used with (2), (4), and (5) for correcting the intensities in the boundary regions. Then, for each pair of overlapping blocks, the common pixels that are assigned significantly different values are counted. Corrected pixels are considered to be significantly different when their absolute difference exceeds a threshold T_d . Finally, motion is flagged if the number of significantly different pixels exceeds a constant D_{max} , which depends on the number of pixels compared.



Fig. 1. Example of part of a frame subdivided in blocks that overlap each other by one pixel.

B. Interpolation of Missing Parameters

The estimated intensity-flicker parameters are unreliable where local motion has been detected and where the variance of the observed data Y(x, y, t) is below T_n [see (11)]. We refer to these parameters as missing. All other estimated parameters are referred to as known. We want to find estimates of the missing parameters by means of interpolation. We also want to smooth the known parameters because $\alpha_{m,n}(t)$ and $\beta_{m,n}(t)$ are assumed to be smooth. The interpolation and smoothing functions should meet the following requirements. First, the system of intensity-flicker correction should switch itself off locally where the correctness of the interpolated missing parameters is less certain. This means that the interpolator should incorporate biases for $\hat{\alpha}_{m,n}(t)$ and $\hat{\beta}_{m,n}(t)$ toward unity and zero, respectively, that grow as the smallest distance to a region with known parameters becomes larger. Second, the reliability of the known parameters should be taken into account. We evaluated a number of interpolation and smoothing techniques and found that successive overrelaxation (SOR) showed the best results.

SOR is a well-known iterative method that can be used for simultaneous interpolation and smoothing [15]. It is based on repeated low-pass filtering. We describe the interpolation and smoothing algorithms for the case of the multiplicative parameters $\hat{\alpha}_{m,n}(t)$. The procedure for the $\hat{\beta}_{m,n}(t)$ is similar and will not be described in detail here. SOR starts out with an initial approximation $\alpha_{m,n}^0(t)$. At each iteration *i*, the new solution $\alpha_{m,n}^{i+1}(t)$ is computed for all (m, n) by computing a residual term $r_{m,n}^{i+1}$ and subtracting this from the current solution

$$r_{m,n,t}^{i+1} = W_{m,n,t}(\alpha_{m,n}^{i}(t) - \alpha_{m,n}^{0}(t)) + \lambda(4\alpha_{m,n}^{i}(t) - \alpha_{m-1,n}^{i}(t) - \alpha_{m+1,n}^{i}(t) - \alpha_{m,n-1}^{i}(t) - \alpha_{m,n+1}^{i}(t))$$
(12)

$$\alpha_{m,n}^{i+1}(t) = \alpha_{m,n}^{i}(t) - \omega \frac{r_{m,n,t}^{i+1}}{W_{m,n,t} + 4\lambda}$$
(13)



Fig. 2. (a) Set of original measurements that have variable accuracy; the missing measurements have been set to one. (b) Smoothed and interpolated parameters using SOR (500 iterations).



Fig. 3. Global structure of the intensity-flicker correction system.

where $W_{m,n,t}$ are the reliability weights as defined in (11), λ determines the smoothness of the solution, and ω is the so-called overrelaxation parameter that determines the rate of convergence. In our case, the $\alpha^0_{m,n}(t)$ are initialized to the known multiplicative intensity-flicker parameters at (m, n), and to the bias value for the missing parameters. The first term in (12) weighs difference between the current solution and the original estimate, and the second term measures the smoothness. The solution is updated in (13) so that where the weights $W_{m,n,t}$ are high, the original estimates $\alpha_{m,n}^0(t)$ are emphasized. In contrast, when the measurements are deemed less reliable, when $\lambda \gg W_{m,n,t}$, emphasis is laid on achieving a smooth solution. This allows the generation of parameter fields where the *missing* parameters are interpolated and *known* parameters, depending on their accuracy, are weighted and smoothed. Fig. 2 shows a sample result obtained by the SOR interpolation method.

IV. PRACTICAL ISSUES

Fig. 3 shows the overall structure of the system of intensityflicker correction. We have added some operations to this figure that we have not mentioned before and that improve the system's behavior. First, the current input and the previous system output (with global motion compensation) are low-pass filtered with a 5 × 5 Gaussian kernel. Prefiltering suppresses the influence of high-frequency noise and the effects of small motion. Then, local means μ and variances σ^2 are computed to be used for estimating the intensity-flicker parameters. These and the current input are used to detect local motions. Then, the missing parameters are interpolated and the known parameters are smoothed. Bilinear interpolation is used for upsampling the estimated parameters to full spatial resolution. This avoids the introduction of blocking artifacts in the correction stage that follows.

To avoid possible drift due to error accumulation (resulting from the need to approximate the expectation operator and from model mismatches), we bias the corrected intensities toward the contents of the current frame. Equation (2) is therefore replaced by

$$I(x, y, t) = \kappa(a(x, y, t)Y(x, y, t) + b(x, y, t)) + (1 - \kappa)Y(x, y, t)$$
(14)

where κ is the forgetting factor. If we choose $\kappa = 1$, the system



Fig. 4. (a) Frames 16, 17, and 18 of degraded Mobile sequence. (b) Corrected frames.



Fig. 5. Results from *Mobile* test sequence: (a) PSNR of degraded and corrected frames, (b) intensity mean, and (c) intensity variance of the original, degraded, and corrected frames.

tries to achieve the maximal reduction in intensity flicker. If we choose $\kappa = 0$, we find that the system is switched off. A practical value for κ is 0.85.

V. EXPERIMENTS AND RESULTS

We apply the system of intensity-flicker correction to sequences containing artificially generated intensity flicker and



Fig. 6. (a) Frames 13, 14, and 15 of Tunnel sequence. (b) Corrected frames.



Fig. 7. Results from Tunnel sequence: (a) intensity mean and (b) intensity variance of degraded and corrected frames.

real (nonsynthetic) intensity flicker. This first experiment takes place in a controlled environment and allows us to evaluate the correction system under extreme conditions. The second experiment verifies the practical effectiveness of our system in a practical situation and forms a verification to the underlying assumptions of our approach.

For both experiments we use a block size of 30×20 for $\Omega_{m,n}$ for estimating the local mean and variance. The parameters for the local motion detector are $T_d = 5$ and $D_{\max} = 6$. With respect to the parameters for SOR, we set $T_n = 25$ in (11), $\omega = 1$, and $\lambda = 5$. Finally, in (14), we let $\kappa = 0.85$.

A. Experiment on Artificial Intensity Flicker

For the first experiment we used the *Mobile* sequence (40 frames) that contains moving objects and camera pan (0.8

pixels/frame). We added artificial intensity flicker according to (1). To simulate intensity flicker, the parameters at each spatial location were taken from second-order two-dimensional polynomials. For each frame in the test sequence, the coefficients for these polynomials were drawn from the normal distribution N(0, 0.1) [from N(1, 0.1) for the zeroth-order term] to generate the $\alpha(x, y, t)$ and from N(0, 10) to generate the $\beta(x, y, t)$. Visually speaking, this leads to severe amounts of intensity flicker.

Fig. 4 shows several degraded and corrected frames from the test sequence. Fig. 5(a) shows the PSNR of the degraded and correct frames. The average PSNR of the degraded sequence is 23.8 dB and of the corrected frame is 30.8 dB. For some frames, there is an improvement of more than 15 dB. The PSNR is not necessarily a good indicator for the improvement in visual quality and therefore it is not necessarily a good indicator of the visual performance of the proposed flickerreduction algorithm. A more intuitive indicator can be found by examining the variations in frame mean and frame variance. Fig. 5(b) and (c) gives the frame means and variances of the original, degraded, and corrected frames. We see that the frame means and variances of the original sequence are nearly constant and that introducing intensity flicker gives large variations in means and variances. After correction, the variation in frame means and variances has been reduced strongly and they are closer to the original values. This implies that the perceived amount of intensity flicker has strongly been reduced. This is confirmed by visual inspection.

B. Experiment on a Naturally Degraded Film Sequence

For our second experiment, we use a sequence called *Tunnel*, 226 frames long, showing a man entering the scene through a tunnel. There is some camera unsteadiness during the first 120 frames, then the camera pans to the right and up. There is film-grain noise and considerable intensity flicker in this sequence. We used the method described in [16] to estimate the total noise variance, which was 8.9. Fig. 6 shows some degraded and corrected frames from this sequence. Fig. 7 shows that after correction, the fluctuation in frame means and variances has significantly been reduced. Visual inspection confirms that the amount of intensity flicker has strongly been reduced without introducing visible artifacts.

VI. DISCUSSION

This paper introduces a system for correcting intensity flicker that performs well on artificially and naturally degraded sequences. The characteristics of the SOR interpolation make it so that regions containing local motion can be corrected very well and that the intensity-flicker correction system switches itself off gracefully in the case that large image regions contain local motion. In case of global motion other than camera pan, i.e., zoom, the motion detector flags motion everywhere and the system switches itself off. The results presented in this paper were based on software simulations. In broadcasting and in film-restoration environments, real-time implementation of our system is required. Our system has been implemented in hardware and shows good results for a series of old film sequences. The system proved to be very robust in the presence of both local and global motion.

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