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Blotch detection and removal for archive film restoration

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Abstract

Blotch detection and removal is an important issue for archive film restoration. In this work, a two-stage Simplified Ranked Order Difference (SROD) detector that takes local motion changes into consideration has been proposed to increase blotch detection performance. Furthermore a novel pixel-based correction method that determines the new values of blotched pixels from spatio-temporal correlation considering edge information is developed. Experimental results show that the proposed approaches give successful detection and correction performances and outperform previously proposed techniques.

Keywords: Blotch detection; Blotch restoration; Video restoration; Archive film

1. Introduction

Film archives suffer from severe visual artifacts due to various factors. Some chemical operations have been employed to restore certain defects in the past. Emerging digital storage and broadcasting technologies make the digitization of film archives inevitable. After the digitization it is possible to restore these archives using intelligent digital signal processing algorithms. These restoration algorithms mainly aim to improve the subjective visual quality of archive films and also provide higher quality at similar compression rates for storage on digital media. A complete video restoration system typically comprises video segmentation, flicker correction, blotch removal, scratch removal, noise reduction and image stabilization parts. Segmentation of archive films into shots is an important task, since it is required for nearly all restoration methods. Video shot segmentation techniques proposed in [1,2] are particularly designed for B&W archive films and have considerably higher accuracy in degraded sequences compared to conventional methods. Flicker artifacts can be considered as sudden brightness changes that do not belong to the natural scene. These defects should initially be restored to increase performance of further restoration stages. Methods proposed in [3,4] mainly aim to decrease brightness fluctuations to accomplish restoration. Blotches are mainly caused by dust and deformation of film material. Detection and restoration of blotches is explained in the following paragraph in more detail, because it is the main topic of this paper. Line scratches are mainly caused by abrasion of film material with a mechanical part of the film projector and occur in the form of vertical lines, generally retaining the same spatial position over several frames [5,6]. Transparent dust effects and film-grain noise still remain after removing flicker, blotch and scratch defects. These defects should also be restored for enhanced visual appearance as in [7,8]. Stabilization of archive film may be required if the sequence shows fluctuations and it can be carried out using approaches presented in [9,10] for example.

Blotches are significant degradations that mainly originate from the loss of film gelatin and dirt particles covering the film surface. Blotches are basically impulsive noise and lead to discontinuity because they appear randomly in the image sequence and hence the probability of existence of blotches at the same place in succeeding frames is very low. It is possible to consider the blotch removal process as

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a two-stage procedure, of which the first step is the detection of blotch locations and the second step is correcting the detected regions. Several methods have been proposed for the detection stage in the literature [11–14]. The simplest method is (Spike Detection Index-a SDIa) that detects blotch regions using global motion compensated preceding and following frames, by thresholding the minimum of backward and forward squared pixel differences [11]. SDIa is capable of achieving a high-correct detection rate however it commonly results in too many false alarms. To reduce the false alarms that usually arise from edges, morphological post-processing has been proposed in [12]. This post-processing improves the detection rate of SDIa but false alarms caused from local object motion and incorrect global motion compensation are not eliminated adequately. In [13], a ranked order difference (ROD) detector that arranges pixels from motion compensated previous and subsequent image regions in a ranked order, and then applies a three-stage thresholding strategy has been proposed. These three thresholds control the number of correct detections and false alarms; but the difficulty of determining these three thresholds constraints the effectiveness of the ROD method. Therefore, a simplified ROD detector (SROD) that uses only one threshold has been proposed in [14]. This method gives improved detection performance for low-threshold values, but the number of false alarms increases in this case.

For the correction stage, a multi-stage median filter (MMF) that is a concatenation of median-filtering operations can be used to correct the missing data regions as proposed in [15]. A 3-D auto regressive model-based technique for missing data interpolation is proposed in [16]. In [17], a texture synthesis method for computer vision applications has been proposed. This method models texture as a markov random field (MRF) and finds a new pixel value for each unfilled pixel according to the squared difference matching criteria, using a contour-based filling procedure. An exemplar-based image inpainting method for region filling and object removal is proposed in [18]. This method calculates a confidence value for each pixel located on the contour of a defined target region and identifies the surroundings of the pixel with the highest confidence value. This part is then filled on a block basis, using spatial information not located within the target region and having the highest similarity with the parts to be filled. In [19], long-range correlation-based image information restoration has been proposed for restoring lost blocks. This method recovers lost image blocks using a long search region according to a luminance transformation-based MSE criterion for missing blocks.

In this paper, a novel two-stage SROD detector that takes local motion changes into account is proposed. Furthermore, a new pixel-based correction method that determines the new values of blotched pixels from temporal correlation, using a contour-based approach similar to [18] and luminance transformation-based correlation as in [19] is proposed for the correction stage.

2. Blotch detection and removal

The degraded image $I(x, y, t)$ suffering from blotches can be modeled as

$$I(x, y, t) = [1 - b(x, y, t)] \times I_o(x, y, t) + b(x, y, t) \times c(x, y, t), \tag{1}$$

where $b(x, y, t)$ is a detection variable which determines degraded ($b(x, y, t) = 1$) or clean ($b(x, y, t) = 0$) pixels, $I_o(x, y, t)$ is the original (or restored) value, and $c(x, y, t)$ is the observed intensity value of blotched pixels, with (x, y) shows spatial position and t is used as temporal index. The detection stage intends to estimate $b(x, y, t)$ for each pixel. The aim of the correction stage is to find the new (restored) value $I_o'(x, y, t)$ for blotched pixels (pixels for which $b(x, y, t) = 1$).

2.1. Blotch detection

2.1.1. The Standard S-ROD detector

The SROD detector uses data from current, preceding and succeeding frames to determine whether any $I(x, y, t)$ pixel is corrupted or not. The detector takes three vertical pixels of the preceding and three vertical pixels of the succeeding frames into account, and constructs a $\mathbf{P}$ vector using these values in the form of

$$\begin{aligned}\mathbf{P}(x, y, t) = [&I(x, y-1, t-1), I(x, y, t-1),\\ &I(x, y+1, t-1), I(x, y-1, t+1),\\ &I(x, y, t+1), I(x, y+1, t+1)].\end{aligned} \tag{2}$$

A corruption measure for $I(x, y, t)$ can then be determined from $\mathbf{P}$ using the SROD operation given as

$$\mathrm{SROD}(x, y, t) = \begin{cases} \min(\mathbf{P}(x, y, t)) - I(x, y, t), & \min(\mathbf{P}(x, y, t)) - I(x, y, t) > 0 \\ I(x, y, t) - \max(\mathbf{P}(x, y, t)), & I(x, y, t) - \max(\mathbf{P}(x, y, t)) > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The corresponding pixel is flagged as a blotch if $\mathrm{SROD}(x, y, t)$ exceeds a given detection threshold (T) and a blotch mask (b) is constructed as

$$b(x, y, t) = \begin{cases} 1 & \mathrm{SROD}(x, y, t) > T, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

2.1.2. The proposed two-stage S-ROD detector

It has been observed that false detections in SROD are mainly caused by motion effects or non-matching edges. It is therefore proposed in this paper, to utilize a two-stage SROD detector to compensate for such effects. In the proposed scheme, local motion compensation-based SROD detection is carried out after a preliminary standard SROD detection stage. It is shown that the proposed approach improves the detection performance by eliminating false alarms caused by local motion and edges.

In the proposed approach, initially standard SROD detection is utilized and an initial blotch mask (b_1) is constructed using a comparably low-threshold value $T1$ to ensure that blotches are successfully captured, despite a large number of false alarms. It is more important that no blotch is missed at this stage, as the number of false alarms will be reduced effectively in the following stage. Next, pixel-based local motion compensation is carried out at the locations of blotch candidates given by the initial blotch mask b_1 and a second SROD detector is employed (see Fig. 1), this time with a higher-threshold value $T2$ using local motion compensated pixels. The final blotch mask (b_2) is constructed according to the output of the second SROD stage. Note that, a block (of size ws × ws) is taken around the processed pixel and this block is searched for in a larger search window (of size sw × sw) in the preceding and succeeding frames according to the MSE criterion for local motion compensation. The proposed detection approach is referred to as two-stage SROD.

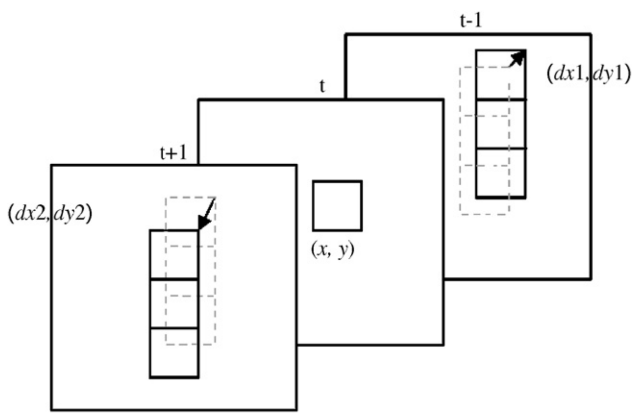

Fig. 1. SROD detection using local motion compensated pixels.

Fig. 2 shows blotch detection results for a sample frame of the Silent test sequence with synthetic blotches, for SROD with two different threshold values and the proposed two-stage SROD. It is clearly seen from Fig. 2 that the proposed two-stage SROD-detection technique reduces the number of false alarms compared to SROD, without losing actually degraded regions.

2.2. Blotch removal

A new pixel-based correction method that restores blotches using spatio-temporal correlation considering spatial detail is proposed in this paper. The proposed method uses a contour-based correction strategy similar to [18] (with a different priority measure) and employs a luminance transformation-based matching criteria similar to [19] (however using neighbouring frames, hence operating temporally).

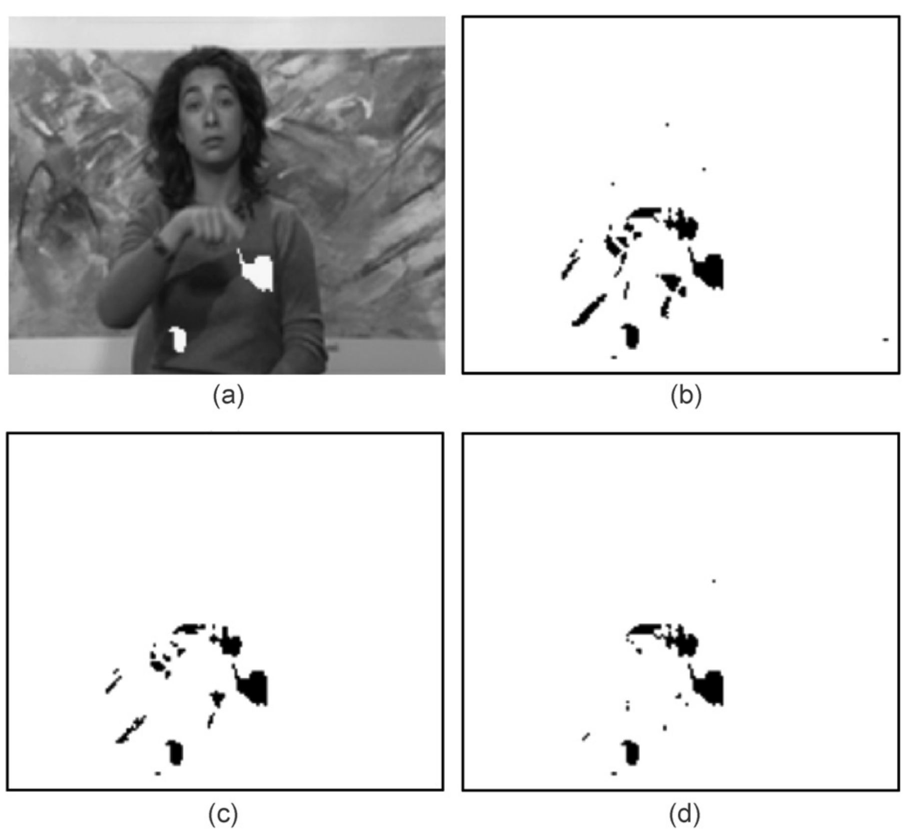

Fig. 2. (a) Image, (b) SROD output ($T1 = 5$), (c) SROD output ($T1 = 10$), (d) two-stage SROD output ($T1 = 5$, $T2 = 10$) for frame number of 67 of synthetically blotched "Silent" test sequence.

The proposed correction method works iteratively as follows:

1. Calculate correction priorities for each pixel on the contour of the blotch mask and decide which pixel(s) should be corrected first.

2. Correct the corresponding pixel(s) and update the blotch mask.

3. Go to Step 1 if blotch mask includes any more pixel(s), else finish the correction.

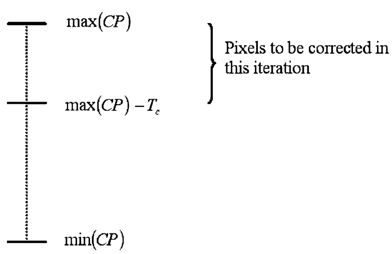

Fig. 3. Range of pixels to be corrected at the current stage.

2.2.1. Correction priority

In order to prevent any bias and correctly restore the spatial structure, pixels contributing to important structural information (such as edges or textures) should be corrected before pixels falling into flat regions. In other words pixels with high-spatial detail should have a higher priority. For this purpose, a correction priority (CP) measure is calculated for each pixel located on the contour of the blotch determined by the blotch mask b_2 in order to decide the correction order. For each pixel located on the contour of the blotch, a CP value is calculated from the difference of maximum and minimum pixel values located outside the blotch in a block of size 3×3, as given

$$\mathrm{CP}(x, y) = \max(I(x+i, y+j)) - \min(I(x+i, y+j)),$$
$$i, j = \{-1, 0, 1\} \ \forall b_2(x+i, y+j) = 0. \tag{5}$$

High or low values of CP indicate whether a pixel is located in a spatially detailed regions or not. The calculated CP values are sorted by decreasing number and the most

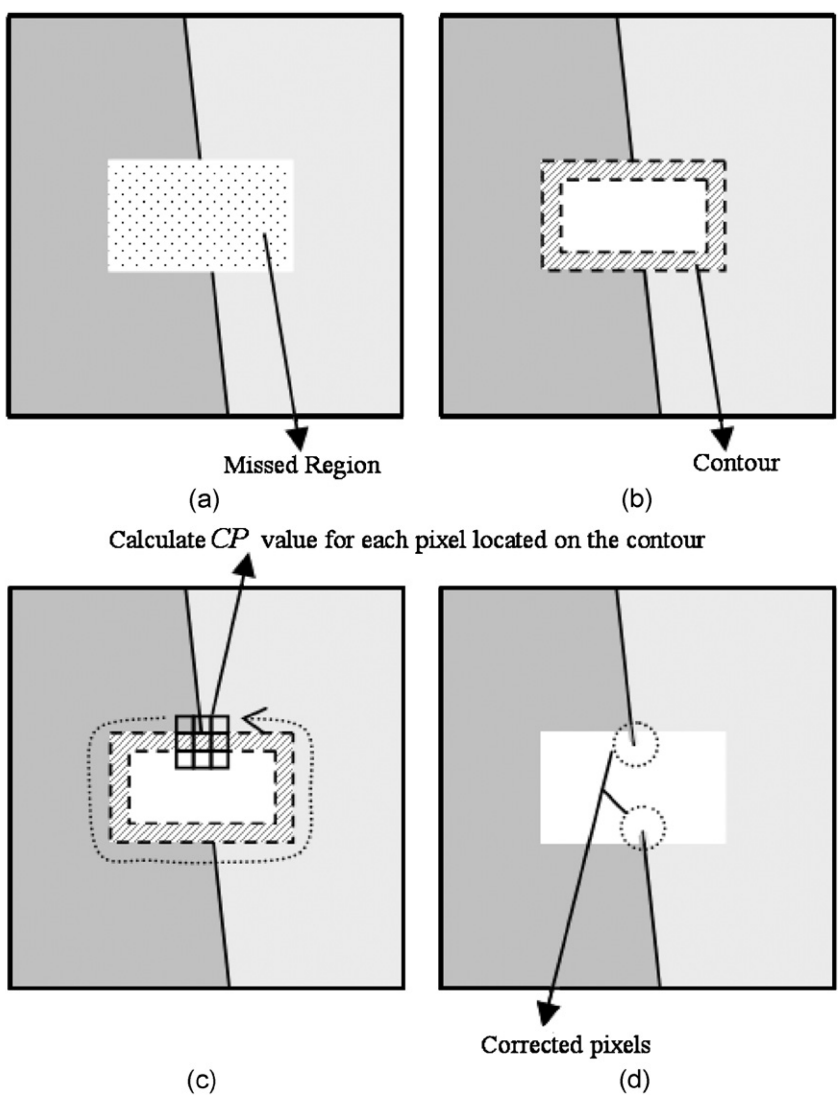

Fig. 4. Calculation of correction priority measure and correcting strategy.

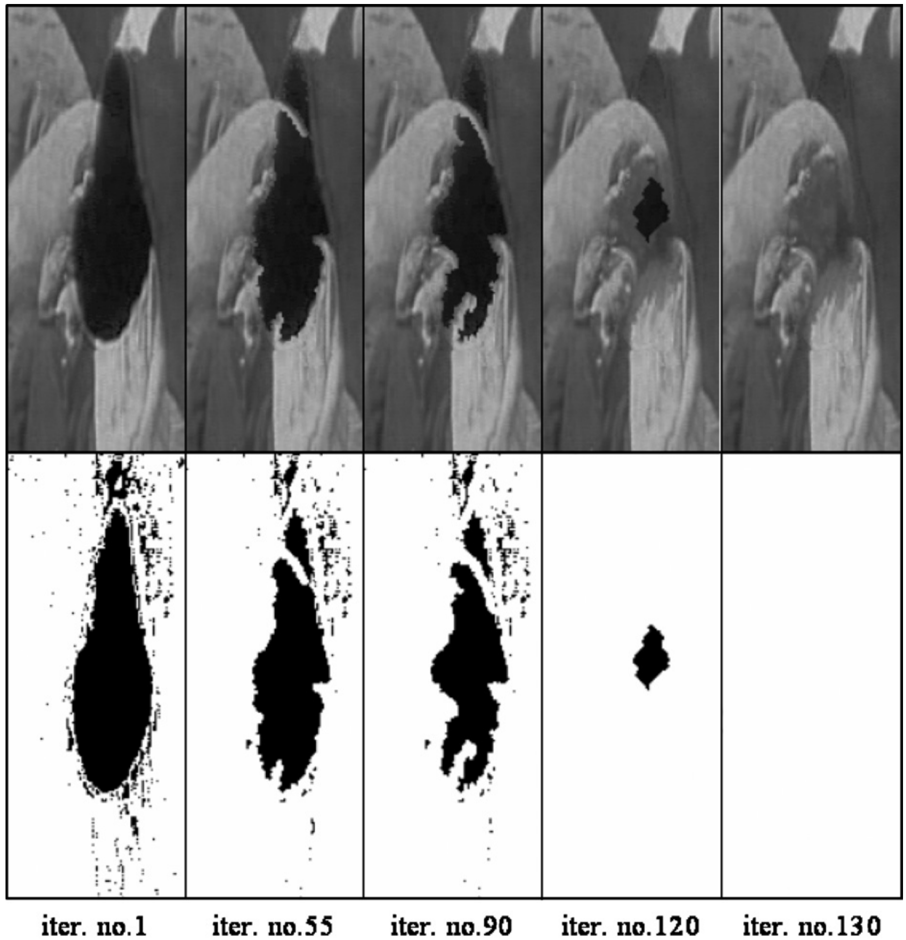

Fig. 5. Different iterations of the correction priority-based restoration for a given image frame.

important pixels are decided using a threshold (T_c) as shown in Fig. 3. This figure shows the CP values sorted from high to low of blotched pixels. All pixels, that have CP values that are at most T_c away from the maximum value, i.e. max(CP) are corrected at the current stage (iteration). Note that, therefore the correction is carried out according to the importance order of corrupted pixels.

After the correction operation, the b_2 mask is updated removing corrected pixels and the correction stage is repeated until there are no more pixels to be corrected. A sample drawing of the correction priority measure calculation and correction strategy is shown in Fig. 4. Here, Fig. 4a shows a sample blotched region. Fig. 4b shows how the contour of the blotched region is constructed. Fig. 4c shows the calculation of CP values for pixels located on the counter. Fig. 4d shows the locations with highest priorities that are corrected firstly.

An example correction priority-based restoration process for a blotched area of an image frame for the given iteration numbers are shown in Fig. 5. As it is seen from Fig. 5, the proposed correcting priority operation finds pixels that are located in spatially detailed regions (particularly edges) and these are filled with higher priority. At each iteration typically blotched pixels located on the blotch counter having the highest CP values are corrected so that the correction process initially reconstructs regions with high spatial detail, avoiding these regions to be influenced by flat regions to recover the missing parts much more correctly.

2.2.2. Correction of pixels

The proposed pixel correction method uses a luminance transformation-based matching criteria similar to [19] with spatio-temporal information. The proposed method is operated for a given pixel as follows:

1. Take a square window around the pixel position (local window).
2. Find the best-matching luminance-transformed remote window within larger search windows of preceding and succeeding image frames for the local window; skipping all blotched regions (Note that the centre pixel of the remote window should be non-blotched).

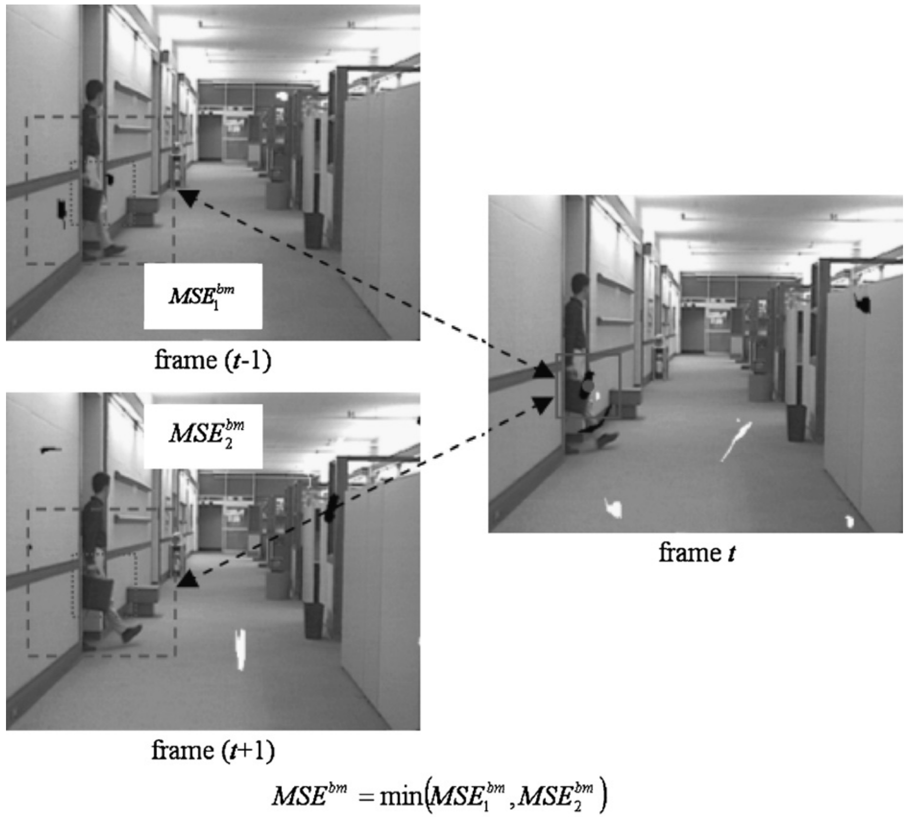

Fig. 6. Best-matched remote window searching strategy from previous and next image frames.

3. Put the centre pixel of the best-matched luminance-transformed remote window to the corrected image.

In this work, MSE is used as a matching criterion in the form of

$$\mathrm{MSE} = \frac{1}{p_u}\sum_{i=1}^{M}\sum_{j=1}^{M}[(1-m^r(i,j)) \times (1-m^l(i,j)) \times (l(i,j) - v(r(i,j)))]^2,$$

$$p_u = \sum_{i=1}^{M}\sum_{j=1}^{M}[(1-m^r(i,j)) \times (1-m^l(i,j))], \qquad (6)$$

where p_u is the total number of used pixels, M is the window size, m^r is the remote window blotch mask, m^l is the local window blotch mask, $l(i,j)$ is a local window pixel, $r(i,j)$ is a remote window pixel, and $v()$ is the luminance transform. The best matched remote window searching procedure is executed as shown in Fig. 6. This figure shows the best match to an example region in the current frame, in the previous and next image frames, within the shown larger search windows. To match the remote window to the local window using the MSE criterion, a first-order polynomial function as given in (7) is used as the luminance transform, similar to [19].

The first-order polynomial function used as luminance transform can be formulated as

$$v(r(i,j)) = \alpha_0 + \alpha_1 \times r(i,j),$$
$$\partial\mathrm{MSE}/\partial\alpha_0 = 0,$$
$$\partial\mathrm{MSE}/\partial\alpha_1 = 0. \qquad (7)$$

In this equation a_0 and a_1 can be denoted as additive and multiplicative luminance transform coefficients, respectively, and these coefficients are computed as given

$$\alpha_1 = \frac{p_u\sum_{i=1}^{M}\sum_{j=1}^{M}(1-m^r(i,j))\times(1-m^l(i,j))\times r(i,j)\times l(i,j) - [\sum_{i=1}^{M}\sum_{j=1}^{M}(1-m^r(i,j))\times(1-m^l(i,j))\times r(i,j)] \times[\sum_{i=1}^{M}\sum_{j=1}^{M}(1-m^r(i,j))\times(1-m^l(i,j))\times l(i,j)]}{p_u\sum_{i=1}^{M}\sum_{j=1}^{M}(1-m^r(i,j))\times(1-m^l(i,j))\times r^2(i,j) - [\sum_{i=1}^{M}\sum_{j=1}^{M}(1-m^r(i,j))\times(1-m^l(i,j))\times r(i,j)]^2},$$

$$\alpha_0 = \frac{1}{p_u}\left[\sum_{i=1}^{M}\sum_{j=1}^{M}(1-m^r(i,j))\times(1-m^l(i,j))\times l(i,j) - \alpha_1 \times \sum_{i=1}^{M}\sum_{j=1}^{M}(1-m^r(i,j)) \times(1-m^l(i,j))\times r(i,j)\right]. \qquad (8)$$

The new value of a blotched pixel is then computed as

$$I'_o(i,j) = v(r_{\mathrm{bm}}((M+1)/2, (M+1)/2)),$$
M is an odd number. (9)

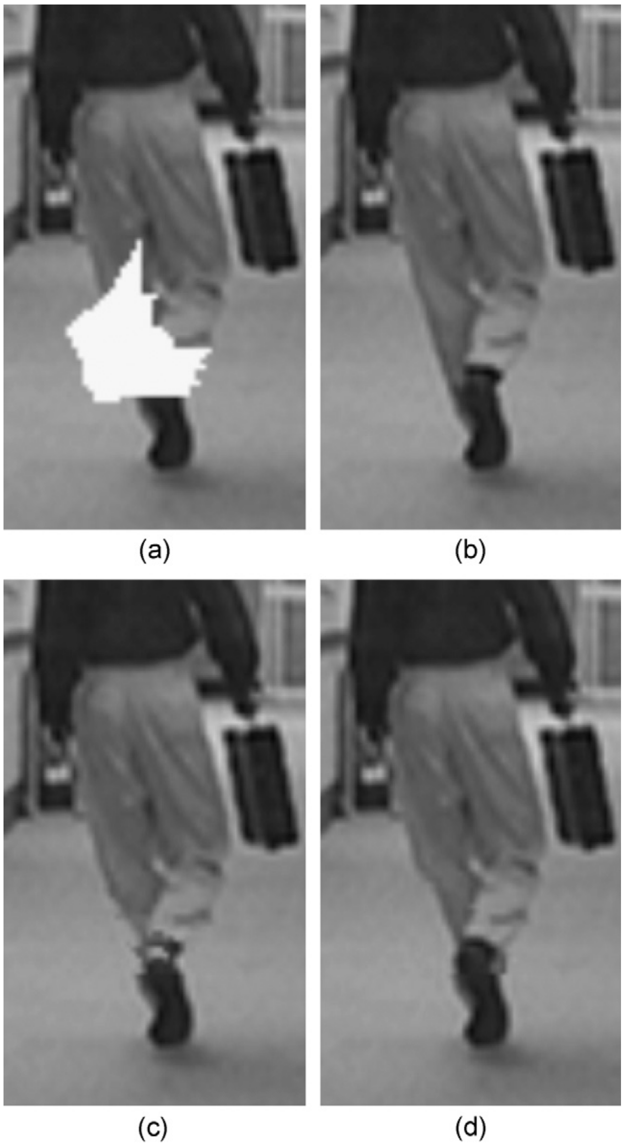

Fig. 7. Correction results for a part of frame no. 67 of the Hall Monitor sequence: (a) corrupted, (b) original, (c) CBCM [20], (d) proposed correction method.

Here, $I_o'(i, j)$ is the corrected pixel value, and r_{bm} is the best-matched remote window. Correction results for a part of frame no. 67 of the "Hall Monitor" sequence are shown in Fig. 7 to give an idea about the visual performance of the proposed correction method. The correction result of the contour-based correction method (CBCM) without spatial priority (i.e. when blotched pixels are corrected via a contour-based onion-peel strategy) as proposed in [20] is also given for this image frame for comparison. Note that part of the artificially distorted region in this frame does not have real image correspondences in preceding and succeeding frames because of excessive local motion. Nonetheless, the blotch is successfully corrected with the proposed approach providing a reasonable visual appearance, using best-matching parts from available regions. It is seen from Fig. 7 that the proposed correction strategy successfully preserves edge information during the correction process.

3. Experimental results

Blotch detectors are generally compared in the literature using receiver operating characteristics (ROC). ROC, plots the correct detection rate (CDR) versus false alarm rate (FAR) for all possible variations of one parameter for a given method. CDR and FAR expressions are defined as

$$\mathrm{CDR} = \frac{N_{\mathrm{C}}}{N_{\mathrm{C}} + N_{\mathrm{M}}}, \quad \mathrm{FAR} = \frac{N_{\mathrm{F}}}{w \times h}, \tag{10}$$

where N_{C}, N_{M} and N_{F} show the number of correctly detected, missed, and falsely detected pixels, respectively. Here $(w \times h)$ is the image size.

Fig. 8 shows ROC curves obtained for artificially corrupted "Silent" test sequence using SDIa [11], SDIa with post-processing as proposed in [12], SDIa with segmentation-based post-processing as proposed in [20], SROD [14] and the proposed two-stage SROD method. It is seen in Fig. 8 that the proposed two-stage SROD method improves the correct detection rate of SROD and also reduces the false detection rate outperforming SDIa as well as SDIa with post-processing.

Although the SDIa method with segmentation-based post-processing as proposed in [20] gives better ROC curves in artificially corrupted sequences, it has been observed that the method proposed in [20] can give an insufficient performance in archive film sequences due to fixed segmentation and completeness thresholds utilized in [20], which in particularly results in the miss of partly transparent blotches. On the other hand, the proposed two-stage SROD detector has been found to even detect partly transparent blotches successfully. Detection performance of the proposed two-stage

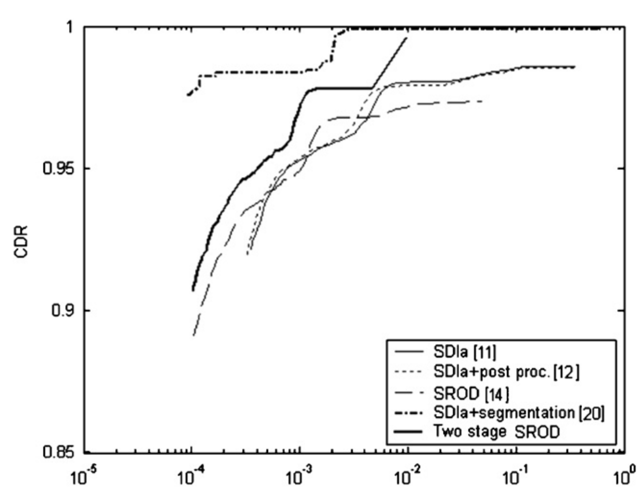

Fig. 8. ROC curves results for blotch detection methods.

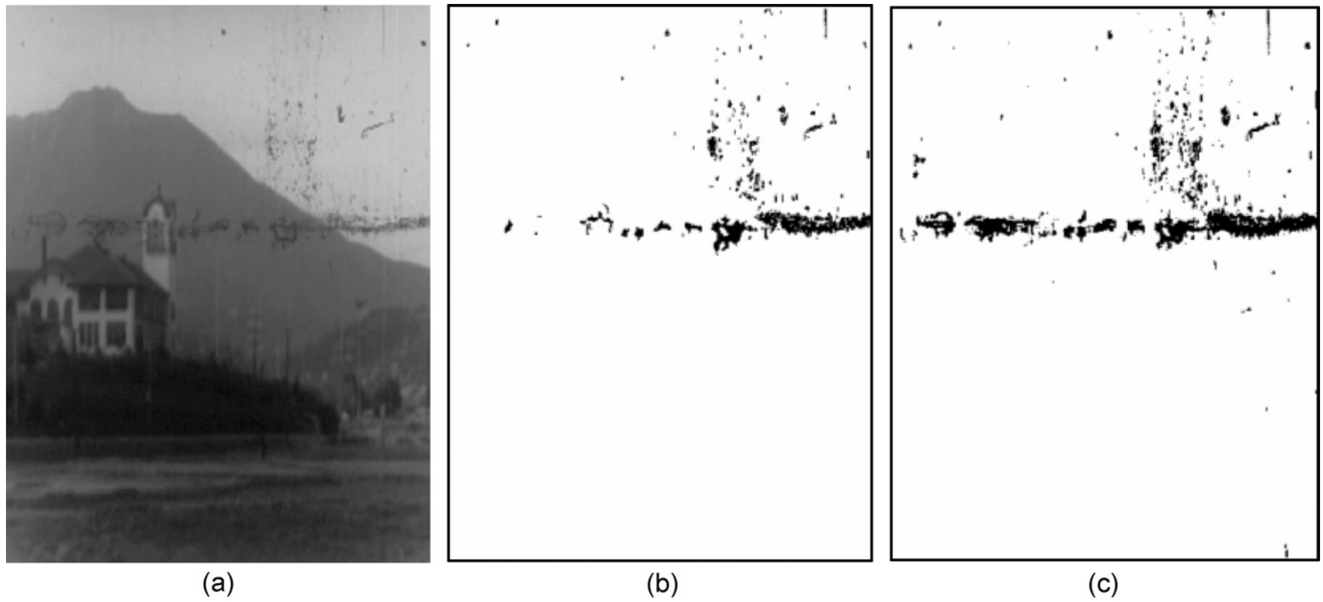

Fig. 9. (a) Original image frame, and detection performances for (b) SDIa method with segmentation-based post-processing [10], (c) proposed two-stage SROD method.

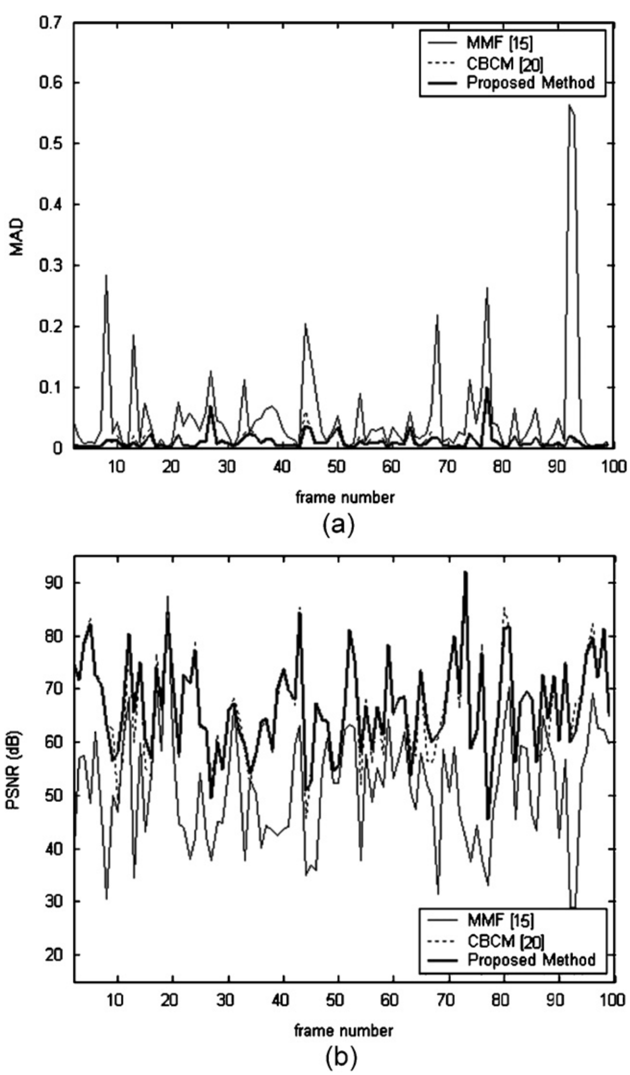

Fig. 10. (a) MAD, and (b) PSNR results for the "Silent" test sequence.

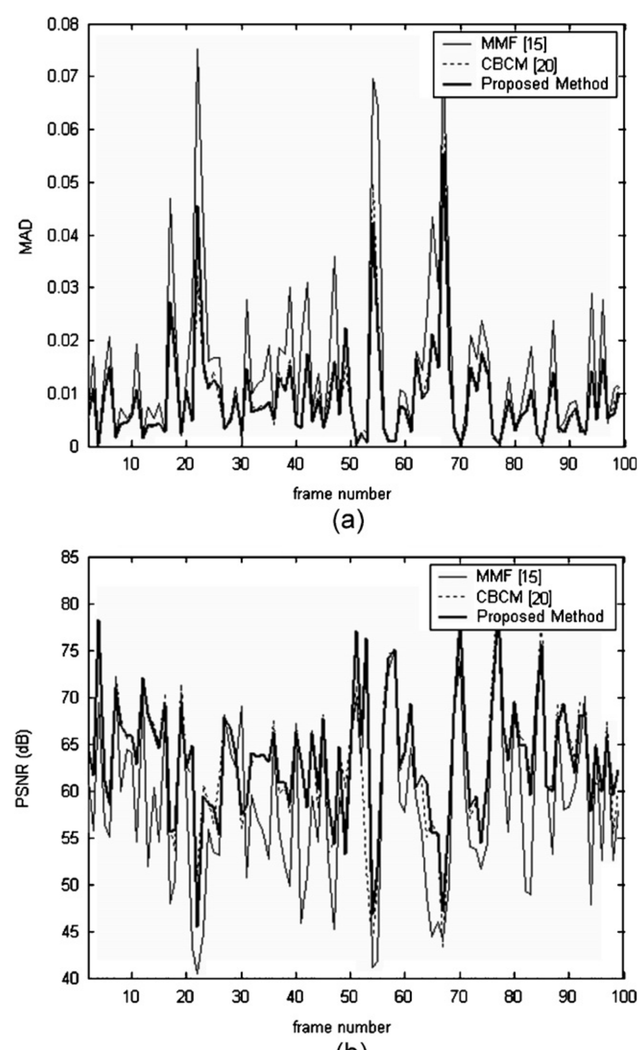

Fig. 11. (a) MAD, and (b) PSNR results for the "Hall Monitor" test sequence.

Table 1. Mean values of the MSE and PSNR results for the “Silent” and “Hall Monitor” sequences

	“Silent”			“Hall Monitor”		
	MMF [15]	CBCM [20]	Prop. Method	MMF [15]	CBCM [20]	Prop. Method
PSNR (dB)	51.27	66.32	68.85	58.68	63.20	63.48
MAD	0.053	0.011	0.010	0.015	0.091	0.092

SROD method and the SDIa method with segmentation-based post-processing [20] for frame no. 45 of the “Mount” archive film that includes transparent blotches are given in Fig. 9. As seen from Fig. 9, the method proposed in [20] cannot detect most of the partly transparent blotches because of transparency (look around the building in the image), consequently visual degradations cannot be restored effectively. The proposed approach is seen to successfully detect even partly transparent blotches.

The correction performance of the proposed approach is compared to MMF [15] and the CBCM without spatial priority [20]. To provide objective criteria, the minimum absolute difference (MAD) and peak signal-to-noise ratio (PSNR) metrics are used. MAD and PSNR values for corrected “Silent” and “Hall Monitor” test sequences are given in Figs. 10 and 11, respectively. Note that these sequences are artificially blotched and then corrected with the corresponding methods, while the MAD and PSNR measures are computed against the original image frames. A low MAD and a high PSNR value is desired for better performance. These figures show that the proposed correction method gives considerably better results compared to MMF in the overall. While the proposed method gives nearly the same MAD and PSNR results as [20], the visual quality obtained by the proposed correction method is much better (as seen also in Fig. 7).

In Table 1, the average MAD and PSNR results for the “Silent” and “Hall Monitor” sequences are given for the compared methods. These results also confirm that the proposed method outperforms MMF and gives slightly better objective quality measures than [20].

4. Conclusion

In this work, new detection and correction methods for blotch restoration are proposed. A two-stage SROD detector that takes local motion changes and non-matching edges into consideration has been proposed to increase the blotch detection performance of the standard SROD approach. Pixel-based local motion compensation is carried out at the locations of blotch candidates detected by the initial SROD and a second SROD detector (with a higher threshold) is employed to make the final decision. Furthermore a novel pixel-based correction method that determines the new values of blotched pixels from spatio-temporal correlation considering important structural information is developed. Experimental results show that the proposed approaches give successful detection and correction performances and outperform previous techniques used for comparison.

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