Novel Post-Processing Methods used in Detection of Blotches in Image Sequences

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Summary
Blotches are the common artifacts in degraded motion picture sequences. They are usually caused by placing dust and dirt on film surfaces as well as abrasion of film materials. Blotches are seen as dark and bright flashes spreading through the frames randomly. The *spike detection index* (SDIa) method is the simplest approach used to detect these artifacts. However, the drawback of SDIa method is that when the motion vectors are not precise enough in some points (*e.g.* in edges of moving objects) these points might be declared as blotches too. This situation can also occur in areas containing a high amount of noise. To overcome these difficulties, two post-processing methods are proposed in this paper. In the first method, the edge points are first omitted from the set of detected points and then to restore true edges, the constrained dilation algorithm is applied. In the second method, we use the local average error value in the detection process. According to low intensity variations in blotch areas, the points with relatively close intensity values are used in the averaging process. Additionally, the combination of SDIa and AR methods are proposed to be used in rather large blotch regions to achieve better detection results. Moreover, to implement the intensity interpolation stage, we propose to use adaptive block sizes to achieve better results. In this paper, a performance comparison among the available methods of detection is stated which clearly shows the superiority of the proposed methods.

Key words:
Video restoration, blotch detection and interpolation, SDIa detector, AR model.

1. Introduction

Many of old archived films and video sequences have undergone degradation caused by aging, bad function of display devices, placing dust, and etc. The degradation is seen as various artifacts in motion picture sequences. To improve the visual quality (and also the efficiency of compression algorithms), removing these artifacts is an essential in building ditital archives and in transmitting video information. One of the common problems in degraded motion picture sequences is the existence of blotches or “dirt and sparkle”. They are mainly caused by either placing dust or dirt on film surfaces or abrasion of film materials. Blotches are seen as bright and dark flashes spreading through the frames randomly. There are two main approaches to remove blotches, simultaneous [1] and modular [2] that is regarded here. In the modular method, the detection of blotch locations and the correction of intensity values (in those points) are done in separate stages. In the detection stage, usually an estimation of the actual intensity value is made for each point and if its difference from the observed intensity value is larger than a predetermined threshold, that point is declared as blotch. As it is assumed that blotches are not repeated in the same location in consecutive frames, the corresponding points in previous and next frames are used in the estimation process. To make the estimation process more precise, motion of points must be considered and compensated. Therefore, the motion estimation is usually the first stage of the restoration process.

Let $y(\mathbf{x})$ represent the original uncorrupted image intensity at location $\mathbf{x}$. The degraded image is modeled by [1]:

$$I(\mathbf{x}) = (1 - b(\mathbf{x}))y(\mathbf{x}) + b(\mathbf{x})c(\mathbf{x}) \quad (1)$$

where $b(\mathbf{x})$ is a detection variable, which is either 1 (at blotch locations) or 0 (otherwise), and $c(\mathbf{x})$ is the observed intensity value in the corrupted region. There are various methods to detect blotch locations (or equivalently $b(\mathbf{x})$ values). The simplest approach is the *spike detection index* (SDIa) introduced by Kokaram [3]. In this method, the intensity value of each point is compared with corresponding points intensity values in neighboring frames and if the absolute values of both differences are larger than a predetermined threshold, the point is declared as blotch. Let $I_n(\mathbf{i})$ be intensity value in location $\mathbf{i}$ of frame n. If the neighboring frames are motion compensated, then the detector output can be determined by:

$$\begin{aligned} e_b(\mathbf{i}) &= I_n(\mathbf{i}) - I_{n-1}(\mathbf{i}) \\ e_f(\mathbf{i}) &= I_n(\mathbf{i}) - I_{n+1}(\mathbf{i}) \\ b(\mathbf{i}) &= \begin{cases} 1 & if\ \left(\left|e_b(\mathbf{i})\right| > e_t\right) and \left(\left|e_f(\mathbf{i})\right| > e_t\right) \\ 0 & otherwise \end{cases} \end{aligned} \tag{2}$$

Using both forward and backward errors prevents occluded or uncovered regions from being declared as blotch.

The main drawback of the SDIa method is that when motion vectors are not precise enough (*e.g.* in edges of moving objects), true edges might be declared as blotches themselves. This situation occurs when simple and common methods like block matching is used for motion estimation. A similar phenomenon can also take place in areas containing a high amount of noise.

In AR method [2] [3], the underlying original image sequence is modeled by a three dimensional autoregressive model (3DAR). If $I(\mathbf{x})$ is the intensity value at location $\mathbf{x} = (i, j, n)$:

$$I(\mathbf{x}) = \sum_{k=1}^{p} a_k I\left(\mathbf{x} + \mathbf{q}_k + \mathbf{d}_{n,n_k}(\mathbf{x})\right) + e(\mathbf{x}) \tag{3}$$

where $a_k\ (k = 1,..., p)$ are AR coefficients and $q_k = (q_{kx}, q_{ky}, n_k)$ determine a neighbor point when there is not any motion. The neighbor points determined by $\mathbf{q}_k$ s construct a *support region*. When motion exists, the support region is shifted by $\mathbf{d}_{n,n_k}$. According to nonstationarity in image sequences, each frame is divided into some non-overlaping blocks and for each block, separate coefficients are computed by normal equations of:

$$\mathbf{Ra} = \mathbf{r} \tag{4}$$

where $\mathbf{a}$ is the coefficients vector and $\mathbf{R}$ and $\mathbf{r}$ include correlation statements. The correlation values are found by averaging in each block.

Due to usage of more points in estimation process and using an optimum linear estimation, this method can produce more accurate results. But when the blotch area occupies a large part of a block, the computed coefficients and so the estimation values would be imprecise. Because of indefinite size of blotches, this method is not a reliable method. Nevertheless, as we will demonstrate, the use of AR method with other methods can improve their performances.

Another interesting detection approach introduced in recent years is the *rank order differences* (ROD) [4]. A simplified version of this method, the *simplified ROD* (SROD) [5], has almost the same performance with much fewer computations. Suppose that for a specific pixel, $p_k\ (k = 1,...,6)$ are the reference pixels , then the output of SROD detector is determined by:

$$\begin{aligned} SROD(i) &= \begin{cases} \min(p_k) - I(i) & \text{if} \quad \min(p_k) - I(i) > 0 \\ I(i) - \max(p_k) & \text{if} \quad I(i) - \max(p_k) > 0 \\ 0 & \text{otherwise} \end{cases} \\ b_{SROD}(i) &= \begin{cases} 1 & \text{if } SROD(i) > T_1 \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{5}$$

where $T_1 \geq 0$ is a predetermined threshold.

Because of using maximum and minimum values of six reference points intensities, to detect blotches with the intensity value near to the original one and to achieve high *correct detection rates*, the threshold must be decreased greatly. This increases the *false alarm rate* especially when the noise power is high. But for lower *correct detection rates* the SROD method has *lower false alarm rates* than SDIa method. Among three mentioned detectors, the SDIa and AR methods have the least and the most computation costs, respectively. According to simplicity of the SDIa method and its advantage in reaching higher *correct detection rates* relative to *simple rank order differences* (SROD) and *auto regressive* (AR) methods, here we propose two post-processing methods to overcome its difficulties. In the first method, at the beginning of the algorithm edge points are omitted from the set of detected points and then to restore the edges of truly detected blotches, a constrained dilation algorithm is applied. In the second method, we use a local average error value in the detection process. According to low intensity variations in blotch areas, the points with relatively close intensity values are used in the averaging process. Additionally, a combination of SDIa and AR methods is proposed to be used in rather large blotch regions to achieve better results.

In the following, in Section II after stating a performance comparison among various methods, the proposed post-processing methods are described. The experimental results of applying different algorithms are stated in Section III. In the correction stage we use AR model and to implement it, we use adaptive block sizes to achieve better results. These concepts are discussed in Section IV. Finally the summary and conclusion remarks are stated in Section V.

2. Proposed Post-Processing Methods for Blotch Detection

In this section first, a performance comparison among various methods of detection is presented and in continue the new post-processing methods for the SDIa detector are presented. Fig. 1 shows performance diagrams of three mentioned detectors obtained for “Diskus” sequence artificially corrupted by blotches. To corrupt the frames, we have used *Markov random fields* as in Kokaram [3].

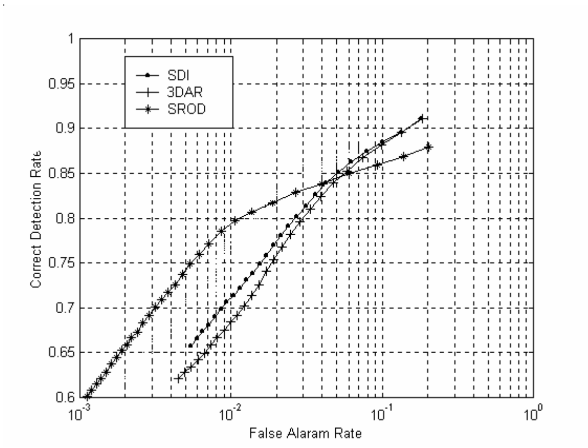

Fig. 1: Performance of three different detectors (frames 30-40 of Diskus sequence).

To comprehend the main drawbacks of these methods, their outputs for an artificially corrupted frame (of Diskus sequence) with actual blotch locations are shown in Fig. 2. As it is seen, in SDIa method many of edges are falsely detected as blotch. In AR method, the existence of blotches has resulted in false decisions in blocks containing them. In this case, the performance of SROD is the best. However its drawback is in false detection of some vertical edges as blotches. This is due to not expantion of reference pixels in the horizontal direction. So if there is some error in the motion estimation stage, the referenced pixels will not be the true corresponding pixels.

As it is mentioned abive, SDIa and SROD methods do not perform well in some edge regions of the frames. According to possibility of using more distributed points for estimation in AR method, we suggest here to join this method with other two methods to resolve the edge region problem. To do this, only common points in SDIa or SROD detector output with AR detector output, will be marked as blotch points. Fig. 3 shows the effect of this strategy when applied in the same frame and parameters as in Fig. 2. Fig. 4 compares the performance of different methods. Here the sequence and the used parameters are as in Fig. 1. As expected, using AR with SDIa is more effective, because of its more false detection in edge regions.

In continue we focus on post-processing methods that increase the efficiency of original methods (especially SDIa). The first algorithm is shown in Fig. 5. In this figure, M1 is a matrix demonstrating the existence, 1, or not existence, 0, of blotch in each point. M2 is a same size matrix that determines edge locations (1 when edge is detected and zero otherwise). To reduce false alarms, edge points determined in M2 are omitted from the set of detected points in M1. But this process also leaves out blotch edges and hence reduces the rate of correct detections. To restore edges in truely detected blotches, the constrained dilation algorithm is applied [5]. In this process the value in a point is set to 1 (blotch) if there is a blotch point in its neighborhood and the intensity difference between them is smaller than a predetermined threshold. This threshold is set to a multiplication of noise standard deviation. The constrained dilation can be used several times but excessive use of it can cause in increasing the false alarms dramatically. To further restrict points added in this process, we can use the condition of being added point in the beginning detection (M1). It must be noted that the concept of removing false alarms due to edges, while preserving blotch edges, are presented in [6]. But in [6] the implementation method is completely different and because of using Markov random fields, it is very time-consuming.

In the second method, to decrease the rate of false alarms in edges and in regions with high amount of noise we use a local average error in each point. According to low intensity variations in blotch areas neighbor points with close intensities are grouped together to compute average error and then this value is assigned to all of them. Fig. 6 shows various stages of this algorithm. At first SDIa method is performed. Its output is error values obtained in each point. Each frame is then divided into non-overlapping blocks and the histogram of each block is computed. To find different regions with different intensities in each block, maximum points of the histogram are found and then points with intensities near each maximum are chosen to form a group. In each group, the mean absolute error is computed and error values of all points of that group are replaced by the mean value. To prevent increasing the rate of false alarms, we can use minimum value of original error and mean error. At last, new error matrix elements are compared with preset threshold and points whose error values are greater than it, are detected as blotch points. The nearness measure in constructing groups is determined by a multiplication of noise standard deviation. To find maximum values we use the condition of being apart at least two times of this value. In the next section we show the efficiency of these methods by applying some experiments.

3. Experimental Results

In this section we present experimental results obtained by using the proposed post-processing methods. In Fig. 7 the performance of implementing these two methods is compared with original SDIa method for two sequences. It is worthmentioning that we have attained similar results for other tested sequences, but due to space saving, just some typical results are stated here. The sequences are artificially corrupted as before. The threshold range is between 0 and 30. In these sequences, the first method has

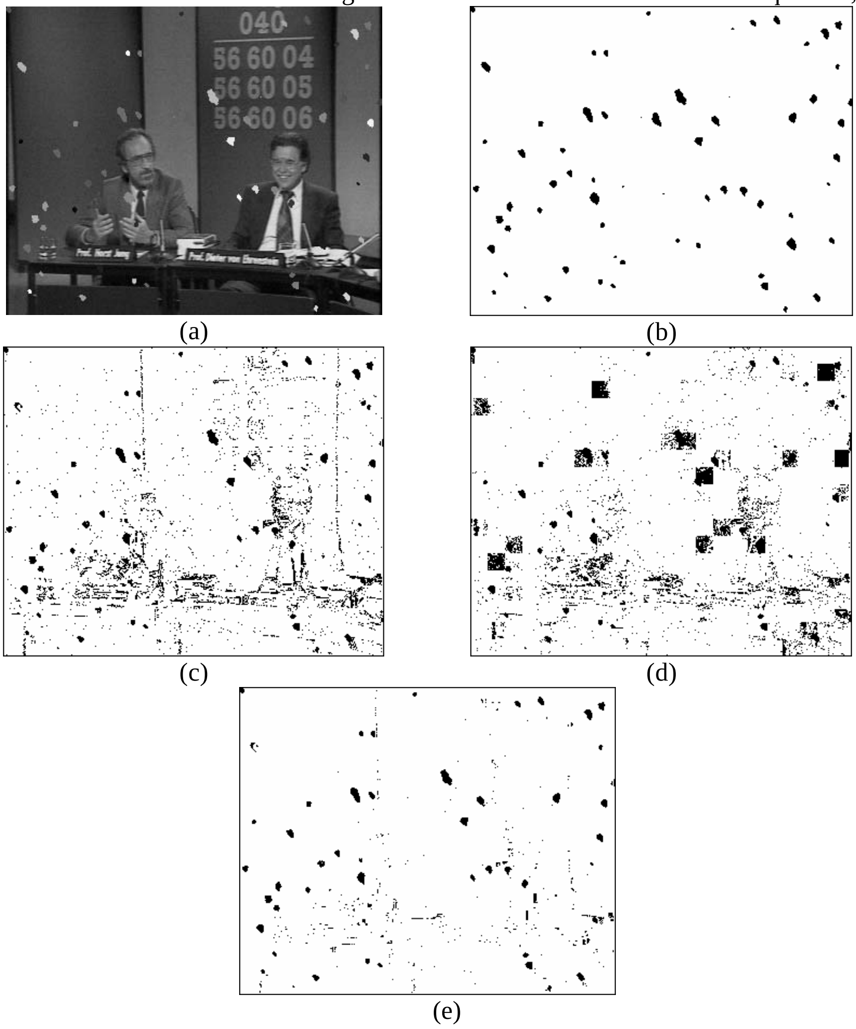

Fig. 2: Results of different detectors for an artificially corrupted frame of Diskus sequence. (a) corrupted frame, (b) actual blotch locations, (c) SDIa output, (d) AR output, and (e) SROD output.

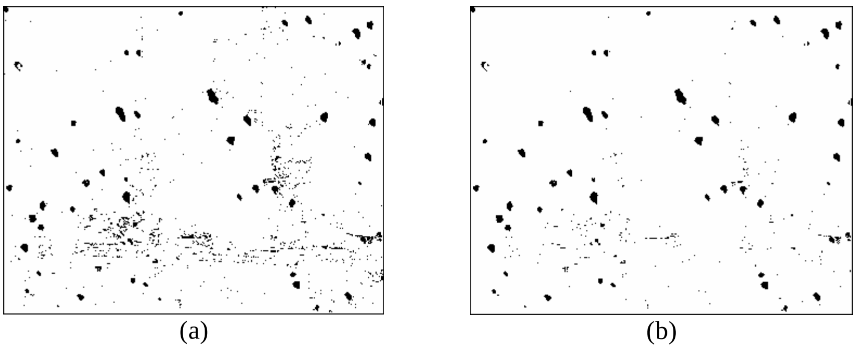

Fig. 3: Effect of using AR with other two methods in the same frame as in Fig. 3. (a) SDIa and AR, (b) SROD and AR.

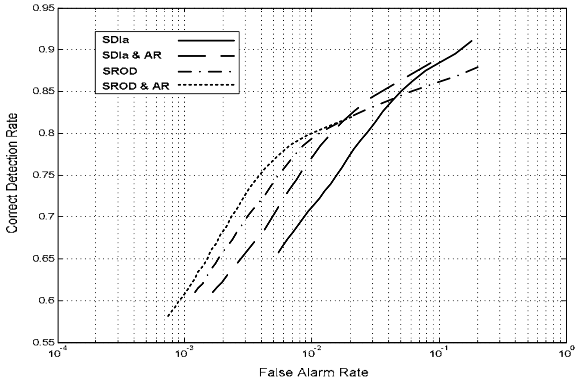

Fig 4.: Effect of using AR with other two methods (frames 30-40 of Diskus sequence).

better performance than the second one, especially when using small thresholds that increases the false decisions. But when the noise power increases, as in some old video sequences, the second method performs better.

Fig. 8 shows blotch detection results for one of the Claire sequence frames obtained by various methods in approximately equal correct detection rates. The effect of two proposed methods in improving the blotch detection performance is apparent.

In Fig. 9 we have shown a part of a real degraded frame and its restored frames (because of space saving the whole frame has not been shown). In the detection stage, we have used SDIa with and without post-processing stage. As it is seen, in original SDIa the details especially in mouth area have been changed but this phenomenon is decreased when applying the proposed methods. Of course the correct detections are reduced too, but decreasing false alarms is dominant.

In the restoration stage, we have used AR method [7] [8], after applying some modifications. The detected points are scanned in a regular pattern. In the first one, a block with a minimum size is considered around the point, then the ratio of correct points to the total block points is computed. If the computed ratio is less than a threshold value, the block size becomes greater. This process continues until above-mentioned ratio reaches a desired value or the block size grows to its maximum allowed size. When block size is selected, the AR estimation is done and estimated values replace previous values of degraded points of that block and these points are marked as correct. This reduces the computational cost of the algorithm significantly. This process is done on the next detected point, that is not corrected in the previous step, and also on other detected points.

The proposed adaptive block size scheme avoids large blocks and so the imprecise estimation results unless there is a need according to existence of large blotches. According to scanning margin points of blotches, at first a large blotch is divided into multiple parts for estimation process leading to increasing accuracy.

In Fig. 10 we have shown various stages of the restoration algorithm for a real degraded frame. For motion estimation we have used a multiresolution block matching algorithm. For a comparison among various methods of motion estimation for corrupted and uncorrupted sequences refer to [9]. Also motion vectors in blotch areas have been corrected to attain more precise vectors and to reduce effect of blotch points in the motion estimation. Here according to small blotches in the frame, advantage of this stage is more dependent to usage of smaller block sizes in blotch points to have a better motion estimation and so a better intensity interpolation. It is obvious that using of the second method for post-processing has reduced false alarms noticeably preventing the corruption of picture details. In this stage 8*8 block size is selected. In the intensity interpolation stage, block sizes vary between 8 and 32. As it is seen, the quality of the frame has improved noticeably. To further improve the quality of the restored frames, the existing scratches should also be removed [10].

3. Summary and conclusion

In this paper we have overviewed three important methods for blotch detection and have given a performance comparison among them. It has been shown that for large blotch areas the SDIa performs better than AR and also in high correct detection rates it performs better than SROD. But for smaller correct detection rates SROD outperforms SDIa. Due to the number of points used for estimation in SDIa and SROD, they do not perform well in some edge regions. To solve this problem, we have combined AR method with SDIa and SROD methods which has resulted in better quality outputs. We have also introduced two new post-processing methods to increase SDIa performance. These proposed methods are able to decrease false alarms caused by edge regions and noise existence. We have also

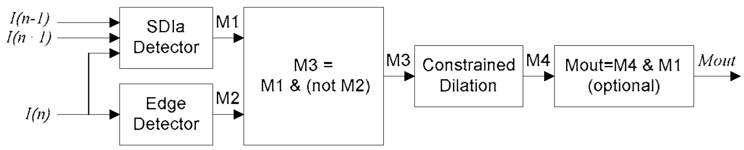

Fig. 5: Block-diagram of the first proposed post-processing method.

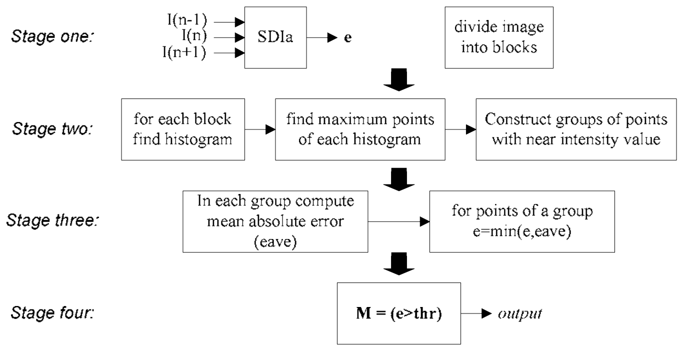

Fig. 6: Block-diagram of the second proposed post-processing method.

shown the capability of these approaches by several experiments. Also in the intensity interpolation stage, we have used adaptive block sizes that further improves the quality of the restored frames.

References

[1] Kokaram, A. C. and S. Godsill, "Joint detection, interpolation, motion and parameter estimation for image sequences with missing data," In IEEE International Conference on Image Processing, pp. 191-194, 1997.

[2] Kokaram, A. C., Motion Picture Restoration, Ph.D. thesis, Cambridge Univ., UK, 1993.

[3] Kokaram, A. C., R. D. Morris, W. J. Fitzgerald and P. J. W. Rayner , "Detection of missing data in image sequences," IEEE Trans. on Image Processing, Vol. 4, pp. 1496-1508, 1995.

[4] Nadenau, M. J. and S. K. Mitra ,"blotch and scratch detection in image sequences based on rank ordered differences," In 5th International Workshop on Time-Varying Image Processing and Moving Object Recognition, 1996.

[5] Biemond, J. P. M. B. Van Roosmalen, and R. L. Lagendijk, "Improved blotch detection by postprocessing," ICASSP-99, Vol. 6, pp.3101-3104, 1999.

[6] Chong, M. N. P. Liu, W. B. Goh, D. Krishnan, "A new spatio-temporal MRF model for the detection of missing data in image sequences ," ICASSP-97, Vol. 4, 2977-2980, 1997.

[7] Kokaram, A. C., R. D. Morris, W. J. Fitzgerald and P. J. W. Rayner, "Interpolation of missing data in image sequences," IEEE Trans. on Image Processing, Vol. 4, pp. 1509-1519, 1995.

[8] Goh W. B., M. N. Chong and D. Krishnan, "Bi-directional 3D auto-regressive model approach to motion picture restoration," in IEEE ICASSP-96, pp. 2277–2280, 1996.

[9] M. Ghadery and S. Kasaei. Improvement and Performance Analysis of Motion Estimation Techniques with Application to Video Restoration. submitted to: Sharif Journal of Science & Technology, 2002.

[10] Kokaram. A.C., "Detection and removal of line scratches in degraded motion picture sequences," In Signal Processing VIII, Vol. I, pp. 5-8, 1996.

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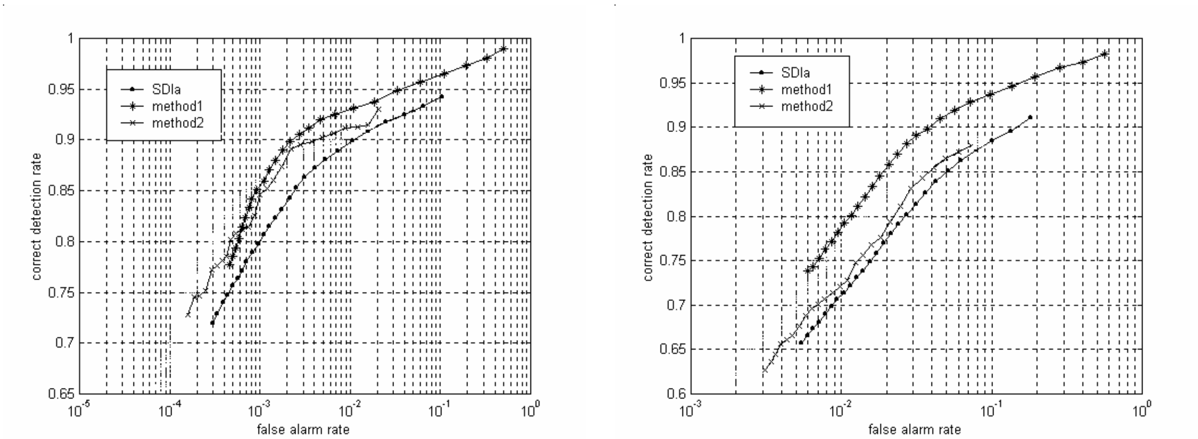
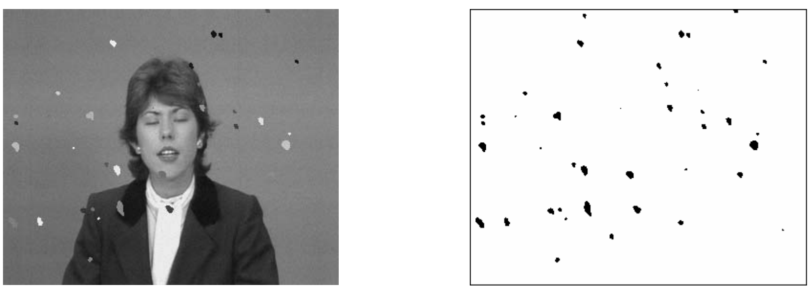


(a) (b)

Fig. 7: Performance of SDIa with and without post-processing methods. (a) first 12 frames of Claire sequence, (b) frames 30-40 of Diskus sequence.



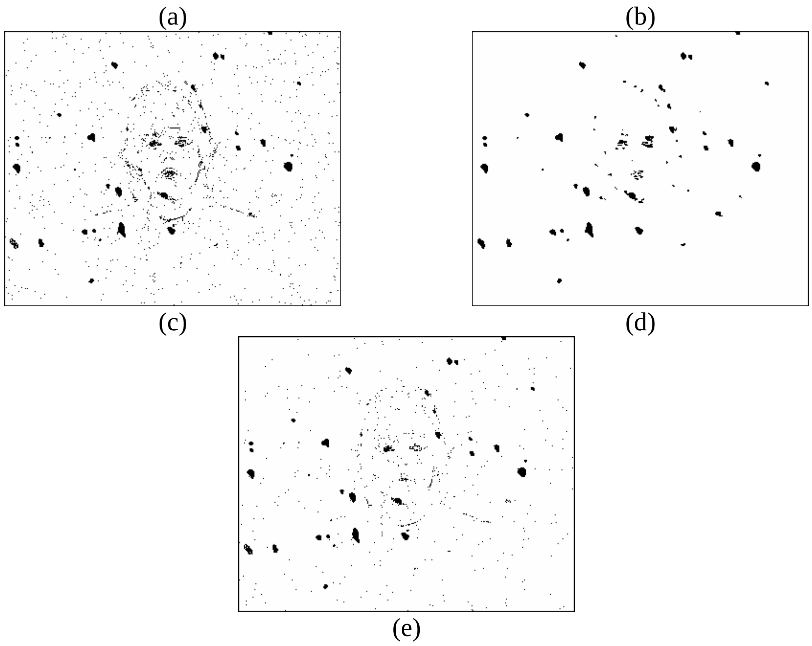


Fig. 8: Detection results in one of Claire sequence frames. (a) corrupted frame, (b) actual blotch locations, (c) SDIa (C.D.=0.9003, F.A.=0.0148), (d) SDIa with first post-processing method (C.D.=0.9126, F.A.=0.0034), and (e) SDIa with second post-processing method (C.D.=0.9065, F.A.=0.0068).

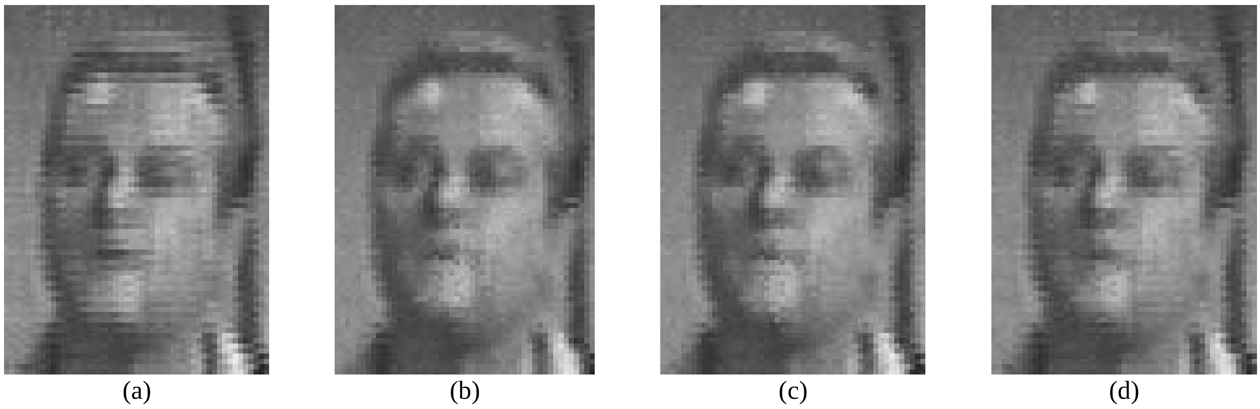


Fig. 9: Comparison between SDIa with and without post-processing. (a) part of a real degraded frame, (b) restored frame with SDIa detection, (c) restored frame with SDIa detection and first post-processing method, and (d) restored frame with SDIa detection and second post-processing method (AR method is used for restoration).

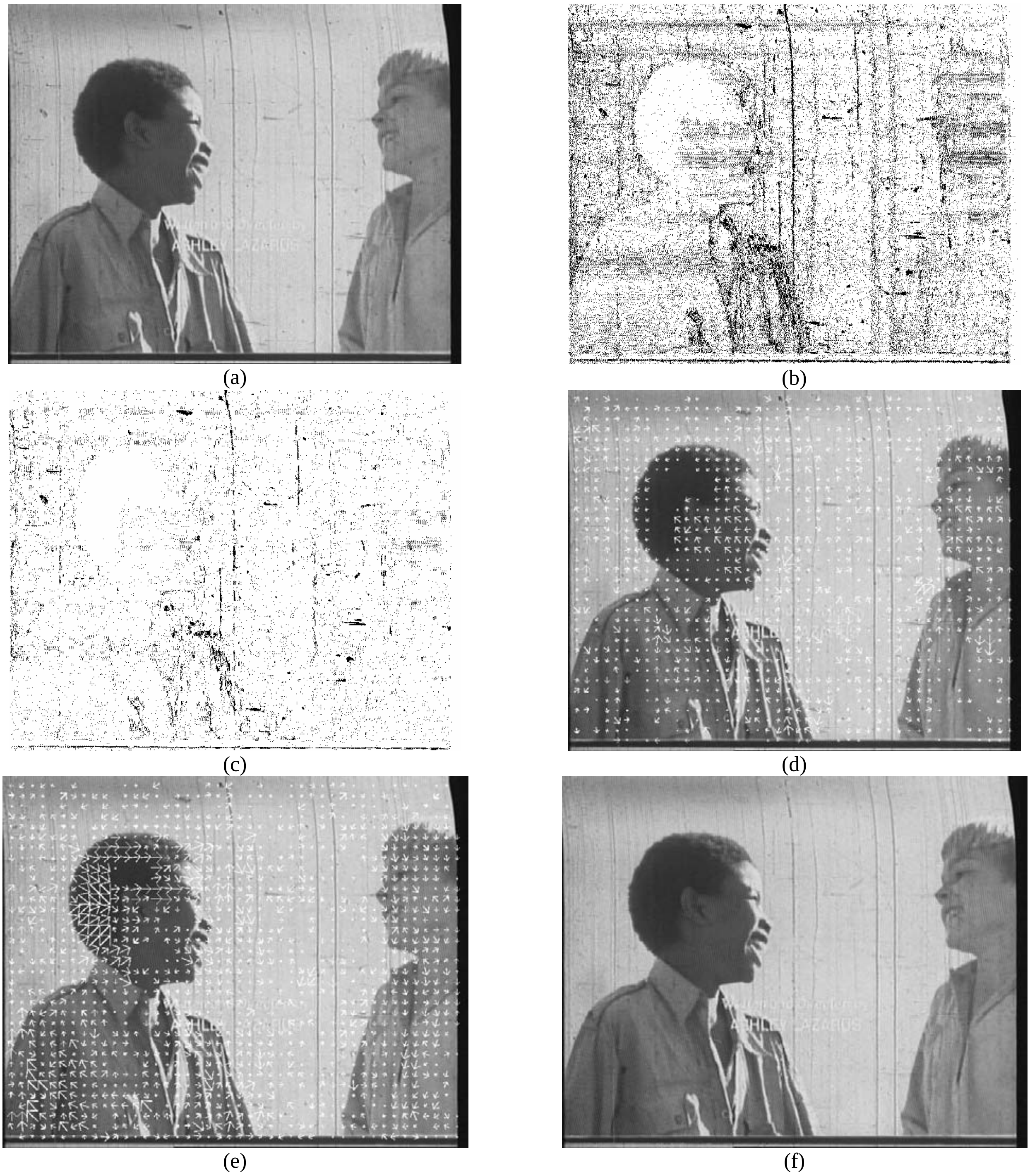


Fig. 10: The main restoration stages. (a) real degraded frame, (b) SDIa detection (threshold=10), (c) applying the second post-processing method, (d)motion vectors relative to past frame after motion correction, (e) motion vectors relative to next frame after motion correction, and (f) the restored frame.