IMPROVED BLOTCH DETECTION IN COLOR OLD FILMS THROUGH A ROBUST PREPROCESSING

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ABSTRACT

Blotches are artifacts that contaminate old films and cause the loss of some information in the film. Their detection is required prior to any restoration. The goal of this paper is to reduce the false alarm rate of the detection. By assuming that blotches correspond to local illumination variations between the degraded frame and its surrounding ones, the novelty of the approach we propose is threefold. Firstly, an appropriate photometric parametric model is adopted. Secondly, a motion analysis involving a robust adaptive cross-correlation measure is used to locally measure the illumination variation. Thirdly, the extension to color sequences is performed. Experimental evaluation shows the efficiency of the proposed preprocessing.

***Index Terms*—** blotch detection, photometric parametric model, motion estimation, outliers.

1. INTRODUCTION

Blotches are artifacts that contaminate old archived films due to bad environmental conditions (humidity, dust . . .) or to the loss of the gelatin covering the film. Consequently, blotches randomly appear in the film as compact stains (resulting from the accumulation of dust) with any shape, size and color. It is mandatory to restore this cultural heritage given its importance. However, the huge amount of degraded films makes difficult a manual restoration. Semi-automatic restoration techniques are preferred: they require a prior digitization of the films and they generally follow two steps. The defects are firstly detected in the degraded images of the sequence. Then, the supposed contaminated areas are corrected by estimating their original content. In this work, we focus on the detection stage. Note that most of the reported detectors tend to exploit the randomness of the blotches [1, 2]. Indeed, blotches produce a temporal discontinuity since they rarely appear at the same position in two successive images. Hence, the past and the next images of the current supposed degraded image are usually used as references to identify blotches. However, moving objects also produce temporal discontinuities. This is the reason why most of the reported detectors compensate the forward and backward motions to discard the temporal discontinuities due to object motions. The detection stage is of a crucial importance in the restoration chain in the sense that it determines which regions of a supposed degraded image should be corrected. More precisely, false alarm rates should be low in order to preserve non-corrupted regions. Several works have been dedicated to the problem of reducing the false alarm rate in digitized versions of old films [1, 3–5]. In this paper, we propose a preprocessing step that preselects suspicious regions and we extend our previous work [5]. Our contribution is threefold. Firstly, a parametric photometric model is considered to locate suspicious regions. Secondly, a novel robust and adaptive matching criterion is used during the motion estimation procedure. Finally, the preprocessing is generalized to the case of color sequences. This paper is organized as follows. In Section 2, the reported works for reducing false alarms are described. Then, the proposed preprocessing method is detailed in Section 3. The experimental evaluation is presented in Section 4. Some conclusions and perspectives are drawn in Section 5.

2. STATE-OF-ART OF PREPROCESSING METHODS

Likewise most of the reported methods, we first assume that the film is black-and-white: after its digitization, a sequence of luminance images of size $L_1 \times L_2$ at time k is obtained. The goal is to locate the blotches in the current image $I^{(k)}$ based on the past image $I^{(k-1)}$ and the next one $I^{(k+1)}$. As previously mentioned, forward and backward Motion Compensation (MC) is performed in order to reduce the temporal discontinuities due to moving objects. However, conventional MC models assume that pixels have constant intensities along their trajectories. This is no longer valid in presence of occlusions, or local illumination variation or even blotches. The impact of such mismatch on blotch detection performance could be handled in two ways: after [1, 4] or prior the detector [3, 5]. Preprocessing-based methods are preferred for their relatively less computational complexity. For instance, in [3], the anisotropic continuity of a pixel trajectory is analyzed among 25 different spatio-temporal directions using a direction cost. The decision whether or not the underlying direction involves corrupted pixels is taken after a training phase. A limitation of this approach is that it does not account for the spatial coherency of blotches, and the noise in the image can be assimilated to blotches. In a previous work [5], we have proposed a preprocessing to identify in the supposed degraded image $I^{(k)}$, the regions that are more likely to be blotched. A conventional blotch detection technique is then applied only on those regions. Our key idea was to consider a blotch as a result of a local illumination variation between the supposed degraded image and the one to be motion-compensated. More precisely, our rationale was to retain an affine motion model that involves illumination parameters and which is robust to the presence of a local illumination variation between both images [6]. This model is defined at each spatial position $\mathbf{r}$ by:

$$I^{(k)}(\mathbf{r}) = h^{(k-1,k)}(\mathbf{r}) I^{(k-1)}(\mathbf{r} + \mathbf{d}^{(k-1,k)}(\mathbf{r})) + b^{(k-1,k)}(\mathbf{r}) \quad (1)$$

where $\mathbf{d}^{(k-1,k)}(\mathbf{r})$ is the displacement of the pixel at the position $\mathbf{r}$ from $I^{(k-1)}$ to $I^{(k)}$, $h^{(k-1,k)}$ is an illumination coefficient that reflects the local brightness variation between both images, and $b^{(k-1,k)}$ allows to compensate the estimation errors of the model parameters. Since the model is local, the three parameters are blockwise estimated. Furthermore, to estimate $\mathbf{d}^{(k-1,k)}(\mathbf{r})$, the Block-Matching Algorithm (BMA) is used, the mean squared error being the matching criterion. After intensive experiments, we have noted that $h^{(k-1,k)}$ has an *atypical* behavior in corrupted blocks. Therefore, we have considered that the *outlier* values of $h^{(k-1,k)}$ are likely related to blotched blocks. To locate such atypical values, we have resorted to a statistical outlier test. It is worth noting that most of the reported statistical tests require the normality of the data, a *prior* step of Gaussianization is carried out thanks to the Box-Cox transform [7]. Among the various statistical outlier tests [8,9], we have retained the Minimum Covariance Determinant (MCD) test for its efficiency and relatively low computational complexity [8]. The same procedure is also applied to detect suspicious regions relatively to $I^{(k+1)}$. Suspicious regions correspond to the regions judged corrupted relatively to both reference images $I^{(k-1)}$ and $I^{(k+1)}$. False alarm rates generated by some conventional blotch detectors (such as the SROD detector [1]) are reduced thanks to this novel preprocessing. In this paper, we propose to further improve the detection rate through a novel preprocessing.

3. PROPOSED METHOD

3.1. Photometric model

We have noted that some blocks judged as suspicious, correspond in fact to an illumination variation that is not due to blotches. Indeed, several intensity variation sources are possible such as lighting conditions. This has motivated us to improve the preprocessing by resorting to a model which is not only robust to the illumination variations but also accounts for real photometric parameters. Moreover, we also suggest to generalize our contribution to color sequences in contrast to the works reported so far. From now on, $I^{(k)}$ denotes an RGB image whose color components are denoted $I_{\mathrm{R}}^{(k)}$, $I_{\mathrm{G}}^{(k)}$ and, $I_{\mathrm{B}}^{(k)}$. Among the proposed photometric models [10, 11], we retain the one described in [11] under the assumption of Lambertian reflectances. It consists in transforming ($I_{\mathrm{R}}^{(k)}$, $I_{\mathrm{G}}^{(k)}$, $I_{\mathrm{B}}^{(k)}$) into ($\bar{I}_{\mathrm{R}}^{(k)}$, $\bar{I}_{\mathrm{G}}^{(k)}$, $\bar{I}_{\mathrm{B}}^{(k)}$) as follows:

$$\bar{I}_{\mathrm{c}}^{(k)}(\mathbf{r}) = \kappa(\mathbf{r}).s_{\mathrm{c}}.\left(I_{\mathrm{c}}^{(k)}(\mathbf{r})\right)^{\gamma}, \quad \mathrm{c} = \mathrm{R, G, B} \quad (2)$$

where

- $\mathbf{r}$ is the spatial position;
- $\kappa(\cdot)$ is a brightness parameter that depends on the local lighting geometry;
- s_{c} is a scaling factor corresponding to the channel c. Indeed, by fixing the lighting geometry and changing the lighting color, the global change of the illumination response at pixel $\mathbf{r}$ is linear relatively to the original intensity $I_{\mathrm{c}}^{(k)}(\mathbf{r})$ [11].
- γ is a constant depending on the acquisition device. In fact, during the acquisition stage, the image data is non-linearly transformed before the storage process. This non-linearity is modeled by a power function transformation (of exponent γ) of the raw sensor responses.

Based on ($\bar{I}_{\mathrm{R}}^{(k)}$, $\bar{I}_{\mathrm{G}}^{(k)}$, $\bar{I}_{\mathrm{B}}^{(k)}$), we aim at locating the suspicious regions concomitantly with the MC stage.

3.2. Detection of suspicious regions

Again, we apply the BMA but this time using the Adaptive Normalized Cross-Correlation (ANCC) as matching criterion. Recently proposed for stereo image matching [12], the ANCC has the advantage of being robust to the illumination variations. Indeed, the authors in [12] define the following normalization steps to eliminate the illumination parameters:
• Firstly, a logarithm transform on the $\bar{I}_{\mathrm{c}}^{(k)}$ provides components linear with respect to the transform parameters :

$$\log(\bar{I}_{\mathrm{c}}^{(k)}(\mathbf{r})) = \log(\kappa(\mathbf{r})) + \log(s_{\mathrm{c}}) + \gamma \log(I_{\mathrm{c}}^{(k)}(\mathbf{r})). \quad (3)$$

• Secondly, a chromaticity normalization eliminates the illumination parameter $\kappa(\cdot)$:

$$\check{I}_{\mathrm{c}}^{(k)}(\mathbf{r}) = \frac{\log(s_{\mathrm{c}})}{\sqrt[3]{s_{\mathrm{R}} s_{\mathrm{G}} s_{\mathrm{B}}}} + \gamma \log\left(\frac{I_{\mathrm{c}}^{(k)}(\mathbf{r})}{\sqrt[3]{I_{\mathrm{R}}^{(k)}(\mathbf{r}) I_{\mathrm{G}}^{(k)}(\mathbf{r}) I_{\mathrm{B}}^{(k)}(\mathbf{r})}}\right). \quad (4)$$

• The problem of the temporal aperture is handled by assigning a weight $w_{\mathrm{c}}^{(k)}(\mathbf{r})$ to each pixel $\mathbf{r}$ in the block $B_{\mathrm{c},(q,r)}^{(k)}$

where (q, r) are the coordinates of the central pixel $\mathbf{p}$. This weight is evaluated relatively to $\mathbf{p}$ according to the bilateral filter [13]:

$$w_{\mathrm{c}}^{(k)}(\mathbf{r}) = \exp\left(-\frac{\|\mathbf{r}-\mathbf{p}\|^2}{2\sigma_d^2} - \frac{(I_{\mathrm{c}}^{(k)}(\mathbf{r}) - I_{\mathrm{c}}^{(k)}(\mathbf{p}))^2}{2\sigma_s^2}\right) \tag{5}$$

where $\|\cdot\|$ is the Euclidean distance, σ_d and σ_s are scale parameters.

• The global scale factors s_{c} are eliminated by subtracting the weighted sum value of the pixels from $\breve{I}_{\mathrm{R}}^{(k)}$, at each pixel $\mathbf{r}$ in the block :

$$\tilde{I}_{\mathrm{c}}^{(k)}(\mathbf{r}) = \breve{I}_{\mathrm{c}}^{(k)}(\mathbf{r}) - \frac{\sum\limits_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} w_{\mathrm{c}}^{(k)}(\mathbf{r}) I_{\mathrm{c}}^{(k)}(\mathbf{r})}{Z(\mathbf{p})} \tag{6}$$

where $Z(\mathbf{p}) = \sum\limits_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} w_{\mathrm{c}}^{(k)}(\mathbf{r})$ is a scaling constant.

Finally, in the resulting log-chromatic system, the ANCC $A_{1,\mathrm{c}}^{(k-1,k)}$ between the block $B_{\mathrm{c},(q,r)}^{(k)}$ and a candidate one $B_{\mathrm{c},(q',r')}^{(k-1)}$ is defined independently from the illumination parameters by:

$$\begin{aligned} A_{1,\mathrm{c}}^{(k-1,k)}(q', r') = \sum_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} & Z_1 Z_1' w_{\mathrm{c}}^{(k)}(\mathbf{r}) w_{\mathrm{c}}^{(k-1)}(\mathbf{r}') \\ & \times \tilde{I}_{\mathrm{c}}^{(k)}(\mathbf{r}) \tilde{I}_{\mathrm{c}}^{(k-1)}(\mathbf{r}') \end{aligned} \tag{7}$$

where $\mathbf{r}' = \mathbf{r} + (q - q', r - r')^\top$ and,

$$Z_1 = \Big(\sum_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} |w_{\mathrm{c}}^{(k)}(\mathbf{r}) \tilde{I}_{\mathrm{c}}^{(k)}(\mathbf{r})|^2\Big)^{-1/2} \tag{8}$$

$$Z_1' = \Big(\sum_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} |w_{\mathrm{c}}^{(k-1)}(\mathbf{r}') \tilde{I}_{\mathrm{c}}^{(k-1)}(\mathbf{r}')|^2\Big)^{-1/2}. \tag{9}$$

In [12], it has been noted that the normalization in the log-chromaticity system may decrease the ability of discriminating between the objects. To alleviate such drawback, it has been suggested to combine the information in the log-chromaticity system with that in the RGB system which contains the original intensities. Therefore, a second expression $A_{2,\mathrm{c}}^{(k-1,k)}$ of the ANCC is firstly derived in a similar way but only involving the initial RGB components:

$$\begin{aligned} A_{2,\mathrm{c}}^{(k-1,k)}(q', r')) = \sum_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} & Z_2 Z_2' w_{\mathrm{c}}^{(k)}(\mathbf{r}) w_{\mathrm{c}}^{(k-1)}(\mathbf{r}') \\ & \times \hat{I}_{\mathrm{c}}^{(k)}(\mathbf{r}) \hat{I}_{\mathrm{c}}^{(k-1)}(\mathbf{r}') \end{aligned} \tag{10}$$

where $\hat{I}_{\mathrm{c}}^{(k)}(\mathbf{r}) = I_{\mathrm{c}}^{(k)}(\mathbf{r}) - \frac{\sum\limits_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} w_{\mathrm{c}}^{(k)}(\mathbf{r}) I_{\mathrm{c}}^{(k)}(\mathbf{r})}{Z(\mathbf{p})}$ and,

$$Z_2 = \Big(\sum_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} |w_{\mathrm{c}}^{(k)}(\mathbf{r}) \hat{I}_{\mathrm{c}}^{(k)}(\mathbf{r})|^2\Big)^{-1/2} \tag{11}$$

$$Z_2' = \Big(\sum_{\mathbf{r}\in B_{\mathrm{c},(q,r)}^{(k)}} |w_{\mathrm{c}}^{(k-1)}(\mathbf{r}') \hat{I}_{\mathrm{c}}^{(k-1)}(\mathbf{r}')|^2\Big)^{-1/2} \tag{12}$$

By averaging the two expressions of $A_{1,\mathrm{c}}^{(k-1,k)}$ and $A_{2,\mathrm{c}}^{(k-1,k)}$ in (7) and (10), the final expression of the ANCC $A^{(k-1,k)}$ is obtained as follows:

$$\begin{aligned} A^{(k-1,k)}(q', r') = \;& \theta \sum_c \frac{A_{1,\mathrm{c}}^{(k-1,k)}(q', r')}{3} \\ & + (1-\theta) \sum_c \frac{A_{2,\mathrm{c}}^{(k-1,k)}(q', r')}{3} \end{aligned} \tag{13}$$

where $\theta \in [0, 1]$ is a weighting coefficient and, $c \in \{R, G, B\}$. Finally, the optimal block $B_{(q^*,r^*)}^{(k-1)}$ is assigned to the current block $B_{(q,r)}^{(k)}$ if:

$$(q^*, r^*) = \arg\max_{(q',r')} A^{(k-1,k)}(q', r'). \tag{14}$$

The optimal value of the ANCC associated to $B_{(q,r)}^{(k)}$ is denoted $A^{*(k-1,k)}_{(q,r)}$.

Once the motion is estimated according to the ANCC measure, our goal is to find the blocks of the current color images at time k that are more likely to be blotched. We assume that a blotch leads to a local illumination variation between both images. We have noted that a contaminated block may have an atypical value of ANCC compared to the values taken by all the remaining blocks. The example depicted in Figure 1 shows that the ANCC values obtained in corrupted blocks are atypical relatively to the neighboring blocks. The inspection of the histogram of the set $\mathcal{A}^{(k-1,k)} = \{A^{*(k-1,k)}_{(q,r)}\}_{(q,r)}$ corroborates the presence of outliers. Consequently, the problem amounts to locate the blocks (q, r) associated to these outliers. In this respect, we resort to a statistical test for outlier detection such as the MCD test after a Gaussianization procedure as shown in the block-diagram of Figure 2.

The same detection procedure is applied by considering the set $\mathcal{A}^{(k,k+1)}$ generated with respect to color images at time $k + 1$. Finally, only regions judged as suspicious with both reference images are taken into account at the blotch detection step. It is worth pointing out that any conventional blotch detector can be used for this stage.

4. EXPERIMENTAL EVALUATION

To evaluate the performances of the novel preprocessing, two sets of experiments are performed on extracts of the real degraded sequence “Les prix”. The goal of these experiments is to firstly evaluate the efficiency of the proposed approach relatively to the preprocessing proposed in [5]. Secondly, we aim to evaluate the performances of the blotch detection with/without the proposed preprocessing. Four state-of-art blotch detectors SDI_a [14], ROD [15], SROD [1] and a detector based on the AutoRegressive (AR) model [14] are

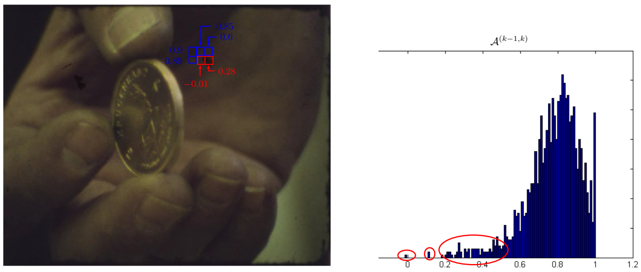

Fig. 1. Distribution of the ANCC values. The first image shows a real degraded image extracted from the "Afrique du sud" sequence. The red blocks are contaminated and the corresponding values of ANCC is atypical relatively to the neighboring blocks (indicated in blue). The second image is the distribution of all values of ANCC where outlier values are highlighted in red.

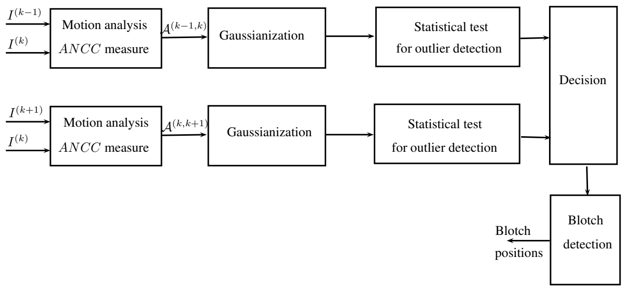

Fig. 2. Block-diagram of the proposed approach.

used. For all experiments, ground truth dirt maps showing the blotch positions in the considered sequences are obtained thanks to a special infrared-film scanner [1]. These maps show dirt as darker areas set against a lighter background and binary ground truth masks are generated through a manual thresholding such that the blotch positions appear as close as possible to the human perception of these defects. The detection performances are measured in terms of good detection rate P_c and false alarm rate P_f and they are visualized thanks to the Receiver Operator Characteristic (ROC) curves which plot P_c versus P_f. The detection performances of a set of images are evaluated by calculating the mean of the correct detection rates in one hand, and the mean of the false alarm rates in the other hand, related to each supposed degraded image. The adjustments of the parameters related to the ANCC measure are chosen according to the experiment results shown in [12] and which are performed on Dolls and Aloe images under different illuminations and different exposures. For instance, the reported results show that the ANCC measure is not so sensitive to the variation of σ_s, and the value 3.8 was retained. The scale σ_d is dependent on the size of the block used in the MC and again experiments show that nearly a constant performance is obtained when the block size is larger than 15×15. We retain this value in order to limit the computational complexity of the ANCC computation and the risk of the presence of multiple motion in a block. The search area size is adjusted to 29×29. The parameter θ determines the weighting between the log-chromaticity color and the RGB color. The value $\theta = 0.7$ is retained in our experiments as it yields an appropriate level of compromise between both color systems according to the results shown in [12].
The threshold values used in SDI_a vary from 1 to 120 by step of 10. Three thresholds are required for the ROD detector. Two thresholds are respectively set to 45 and 55. The third one varies between 1 and 38, likewise the threshold used for the SROD detector. The threshold used for the AR detector varies between 1 and 38 by step of 7. In order to ensure fair comparisons, and since SDI$_a$, the AR based detector, ROD and SROD detectors (without preprocessing) require a prior step of motion compensation before the blotch detection step is performed, the motion is estimated by considering the affine motion model at a first time, and the ANCC measure at a second time. As these detectors and the preprocessing proposed in [5] assume that the analyzed images are gray-level, the detection is performed on each color channel independently of the two others. Then, the detections found for each channel are merged to obtain the final positions of corrupted pixels. By using SDI$_a$, AR based detector, ROD and SROD detectors, the ROC curves depicted in Figure 3 clearly show the benefit drawn from the preprocessing step to reduce the false alarm rate either using the affine motion model or this novel approach. The latter method outperforms the affine motion model based approach. For instance, for the same correct detection rate $P_c = 0.25$ obtained by the SDI$_a$ detector, the approach we propose yields a false alarm rate $P_f = 0.006$ against $P_f = 0.025$ obtained by using the preprocessing proposed in [5]. A subjective evaluation is also depicted in Figure 4 where the detection maps obtained by using the SDI$_a$ detector are displayed. These maps show a noticeable reduction in the false alarm rate (blue pixels in the maps) when using the proposed preprocessing.

5. CONCLUSION AND PERSPECTIVES

In this paper, a preprocessing step designed to reduce false alarm rate generated by classic blotch detectors is proposed. Our contribution in this paper is to firstly adopt a chromatic transformation model that involves real photometric parameters. A generalization to color degraded sequences is also elaborated. Secondly, a robust adaptive normalized cross-correlation measure is retained to estimate the motion between images. Experiments on extracts of a real degraded sequence have shown the efficiency of the proposed approach. This work can be improved by resorting to a multiscale analy-

[1]Made available in `http://stilie.free.fr/research.html`

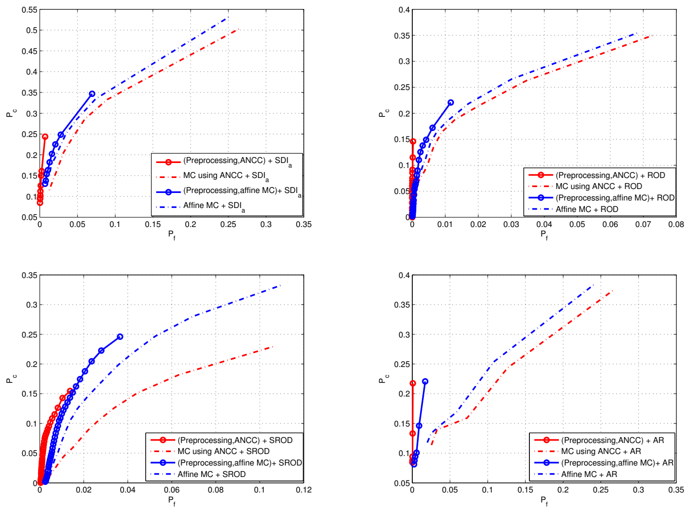

Fig. 3. Detection results using the preprocessing (in solid line) and without preprocessing (in dot line) and four state-of-art blotch detectors. From left to right and from top to bottom: SDI_a, ROD, SROD, AR based detector.

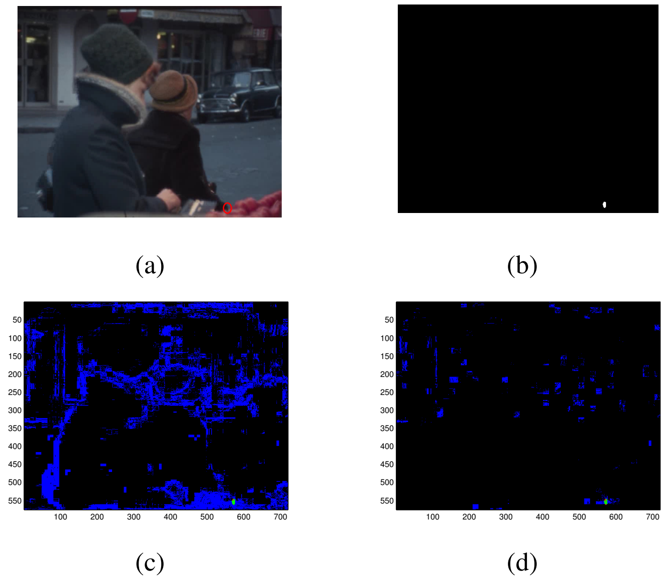

Fig. 4. Detection results using the SDI_a detector. (a) The image #2 of the "Les prix" sequence. (b) Corresponding ground truth map. (c) Results without preprocessing. (e) Results using the proposed preprocessing. Pixels in green: correct detections. In blue: false alarms. In red: missing detections.

sis of the images. This would allow to adapt the size of blocks used in the MC step to the image content.

6. REFERENCES

[1] P. M. B. Van Roosmalen, *Restoration of archived film and video*, Ph.D. thesis, Delft University of Technology, The Netherlands, 1999.

[2] P. Gaughran, S. Bergin, and R. Reilly, "Towards automatic blotch detection for film restoration by comparison of spatio-temporal neighbours," in *AICS'09 Proceedings of the 20th Irish conference on Artificial intelligence and cognitive science*, pp. 114–123. Springer, 2010.

[3] T. Saito, T. Komatsu, T. Ohuchi, and T. Hoshi, "Practical nonlinear filtering for removal of blotches from old film," in *IEEE International Conference on Image Processing, ICIP 99.*, 1999, vol. 3, pp. 164–168.

[4] L. Laborelli S. Tilie and I. Bloch, "A contrario false alarms removal for improving blotch detection in digitized films restoration," *6th EURASIP Conference focused on Speech and Image Processing, Multimedia Communications and Services*, 2007.

[5] H. Ammar-Badri and A. Benazza-Benyahia, "Improving blotch detection in old films by a preprocessing step based on outlier statistical test," in 19^{th} *European Signal Processing Conference. Barcelona, Spain*, 2011, pp. 539–543.

[6] F. J. Hampson and J. C. Pesquet, "Motion estimation in the presence of illumination variations," *Signal processing: Image Communication*, vol. 16, no. 4, pp. 373–381, 2000.

[7] E. P. G. Box and D. R. Cox, "An analysis of transformations," *Journal of Royal Statistical Society, Series B (Methodological)*, vol. 26, pp. 211–252, 1964.

[8] P. J. Rousseeuw and K. V. Driessen, "A fast algorithm for the minimum covariance determinant estimator," *American Statistical Association and the American Society for Quality*, vol. 41, no. 3, pp. 212–223, 1999.

[9] M. Riani, A. C. Atkinson, and A. Cerioli, "Finding an unknown number of multivariate outliers," *Journal of the Royal Statistical Society: series B (Statistical Methodology)*, vol. 71, no. 2, pp. 447–466, 2009.

[10] S. A. Shafer, "Using color to separate reflection components," *Color Research & Application*, vol. 10, no. 4, pp. 210–218, 1985.

[11] G. Finlayson and R. Xu, "Illuminant and gamma comprehensive normalisation in rgb space," *Pattern Recognition Letters*, vol. 24, no. 11, pp. 1679–1690, 2003.

[12] Y. S. Heo, K. M. Lee, and S. U. Lee, "Robust stereo matching using adaptive normalized cross-correlation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 4, pp. 807–822, 2011.

[13] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *IEEE Sixth International Conference on Computer Vision*, 1998, pp. 839–846.

[14] A. C. Kokaram, R. D. Morris, W. J. Fitzgerald, and P. J. W. Rayner, "Detection of missing data in image sequences," *IEEE Transactions on Image Processing*, vol. 4, no. 11, pp. 1496–1508, 1995.

[15] M. J. Nadenau and S. K. Mitra, "Blotch and scratch detection in image sequences based on rank ordered differences," in *Internat. Workshop on Time Varying Image Processing and Moving Object Recognition*, 1996, pp. 1–7.