FAST BLOTCH DETECTION ALGORITHM FOR DEGRADED FILM SEQUENCES BASED ON MRF MODELS

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ABSTRACT

This paper proposes a fast blotch detection algorithm based on a Markov Random Field (MRF) model with less computational load and with lower false alarm rate than the existing MRF-based algorithms. The proposed algorithm can save the computational time for detecting the blotches by restricting the attention of the detection process only to the candidate areas. The experimental results show that our proposed method provides the computational simplicity and an efficient detecting performance for the blotches.

Index Terms— Image restoration, image processing.

1. INTRODUCTION

Many of old films are valuable historical and cultural records. However, most of them have undergone a variety of degradations, which reduce their usefulness. The degradations not only incur a loss of original information of film material due to decay over time, but also make viewers annoyed. The main visual defects are divided into four impairments in degrade film sequences: frame displacement, blotches, line scratches and intensity flickers [1].

Up to the present, film material have been restored generally using traditional film restoration techniques or computer-aided techniques. However, the former does not permit the removal of all kind of degradations and the latter requires a ridiculously high expense and takes several months for the treatment of just one movie. Furthermore, the preservation of degraded film materials at high resolution such as 4K resolution (4096×2160 pixels) has been steadily increasing with the rise of consumer digital video application. Therefore, it is required to construct an automatic digital restoration system that is capable of restoring film sequences at high resolution beyond the above mentioned drawbacks.

The central issue in digital archive restoration is to detect and remove the blotches damaged by dirt and abrasion of the film material. This paper consider an efficient detecting algorithm for the blotches in degrade film sequences. In degraded film sequences, blotches are characterized by the two properties. The first, called temporal discontinuity, means that they rarely located in the same location in two succeeding image frames. The second, called spatial coherency, means that they tend to smooth, and they have intensity values that is uncorrelated with that of pixels in their neighborhood.

Although the performance of the blotch detectors strongly depends on the sequences themselves, it has been found that the Markov Random Field (MRF) approach performs generally better than other existing detectors, for example, SDIa detector, AR detector, and so forth [2, 3]. However, if we apply the existing MRF-based blotch detector on high resolution images, considerably high computational cost is inevitable. Consequently, a fast and efficient algorithm for the blotch detection is required.

In this paper, we propose an efficient algorithm based on an MRF model for detecting blotches with less computational cost and with lower false alarm rate than the existing MRF-based detectors. The main idea is to restrict the attention of the detecting process only to the candidate blotch areas using a significance test. Experimental results demonstrate an efficient detecting performance of the proposed method compared with the existing MRF-based methods.

2. A MARKOV RANDOM FIELD MODEL

In this section, we discusses an MRF model applicable to the spatial coherency of the blotches as *a priori* model [2, 4].

Blotches are detected where temporal discontinuities are detected both in forward and backward temporal directions:

$$D = \begin{cases} 1 & \text{if} \quad (d_f = 1) \cap (d_b = 1) \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

where d_f and d_b denote the blotch detection mask of forward and backward temporal direction, respectively.

An a posteriori probability for a binary blotch mask, given the current frame and a motion-compensated reference frame, is defined. Bayes theorem states that

$$P(D = d|I = i) \propto P(I = i|D = d)P(D = d). \tag{2}$$

The problem for detecting blotches is formulated as a maximum *a posteriori* probability (MAP) estimation problem consisting of two terms: a likelihood model and a priori model.

Consequently, the main object is to find the configuration which maximize Eq. (2) of the detection mask D.

Let S denote the pixel lattice of two adjacent frames and $i(\boldsymbol{r})$ denote the observed intensity at each site $\boldsymbol{r}$ of the lattice S. Let $\mathcal{N}$ denote the first-order neighborhood system on S, and $i(\boldsymbol{mc})$ denote the single motion-compensated pixel of temporal neighborhood in the other frame of the pair.

The likelihood function is defined by [2, 4]:

$$P(I=i|D=d)=\frac{1}{Z_I}\exp\left(\frac{-1}{T}\sum_{\boldsymbol{r}\in S}\left[\alpha'\sum_{\vec{s}\in\mathcal{N}_{\boldsymbol{r}}}(i(\boldsymbol{r})-i(\vec{s}))^2 +\alpha(1-d(\boldsymbol{r}))(i(\boldsymbol{r})-i(\boldsymbol{mc}))^2\right]\right). \quad (3)$$

The prior on the detection frame [4]:

$$P(D=d)=\frac{1}{Z_D}\exp\left(\frac{-1}{T}\sum_{\boldsymbol{r}\in S}\left[-(\beta_1+\psi(i(\boldsymbol{r})))f(d(\boldsymbol{r})) +(\beta_2+\psi(i(\boldsymbol{r})))\delta(1-d(\boldsymbol{r}))\right]\right) \quad (4)$$

where $f(d(\boldsymbol{r}))$ is the number of the four neighbors of $d(\boldsymbol{r})$ with the same value as $d(\boldsymbol{r})$, $\delta()$ is the delta function, and $\psi(i(\boldsymbol{r}))$ denotes a weighting function in moving edges to avoid the temporal discontinuity problem caused by the poorly motion compensated pixels.

Combining Eqs. (3) and (4), and dropping the term from Eq. (3) which is not a function of d, the *a posteriori* distribution can be expressed as

$$\begin{aligned} P(D=d|I=i) &\\ = \frac{1}{Z}\exp\Bigg(\frac{-1}{T}\sum_{\boldsymbol{r}\in S}\Big[&\alpha(1-d(\boldsymbol{r}))(i(\boldsymbol{r})-i(\boldsymbol{mc}))^2 \\ &-(\beta_1+\psi(i(\boldsymbol{r})))f(d(\boldsymbol{r})) \\ &+(\beta_2+\psi(i(\boldsymbol{r})))\delta(1-d(\boldsymbol{r}))\Big]\Bigg) \quad (5)\end{aligned}$$

where α, β_1 and β_2 are the parameters to determine the characteristics of detector.

3. BLOTCH DETECTION ALGORITHM

In this section, we present a fast and efficient detection algorithm for the blotches using the MRF model. The proposed algorithm consists of the four steps: (I) motion estimation, (Ⅱ) estimation of the candidate Blotch Detection Mask (BDM), (ⅠⅡ) moving edge detection, (Ⅳ) solution of the MAP problem.

(I) Motion estimation

In this step, we discuss a motion vector estimation based on block matching. In the representation used for block matching, an image is divided into blocks of size $N_1 \times N_2$ rectangular shape. The search is usually limited to an $(N_1+2\times w)\times(N_2+2\times w)$ block centered on the current block position with fixing the maximum expected displacement to $\pm w$ pixels. For each current block in the current frame, the block in a reference frame that is the most similar is searched according to the minimum MAD criterion defined as

$$\mathrm{MAD}(\boldsymbol{v})=\frac{1}{N_1N_2}\sum_{\boldsymbol{r}\in\mathcal{B}}|I_k(\boldsymbol{r})-I_{k-1}(\boldsymbol{r}+\boldsymbol{v})| \quad (6)$$

where $\mathcal{B}$ denotes an block of size $N_1\times N_2$. Then the estimate of the motion vector is given by

$$\hat{\boldsymbol{v}}=\arg\min_{\boldsymbol{v}}\mathrm{MAD}(\boldsymbol{v}). \quad (7)$$

In order to prevent erroneous motion vectors caused by noise in image sequences, we introduce the method of Boyce [5]. This technique compares the displacement corresponding to the minimum MAD, E_{min}, with the MAD of "no motion", E_0. If the ratio $\gamma = E_0/E_{min}$ is less than some threshold T_0 (here $T_0 = 1.2$), the motion vector is assumed as a spurious match, and thus is set to [0,0]. If the ratio is lager than the threshold, the displacement corresponding to that match is selected.

(Ⅱ) Estimation of the candidate BDM

In this step, we present the candidate blotch detection mask (BDM) consisting of binary labels for each pixel by the threshold calculated by performing the significance test [6]. Given the current frame $I(\boldsymbol{r})$ and the motion-compensated reference frame $I_{mc}(\boldsymbol{r})$, the candidate BDM is computed by a threshold on the squared intensity difference image. The intensity difference image, $Z=\{z_{\boldsymbol{r}}\}$, with $z_{\boldsymbol{r}}=I(\boldsymbol{r})-I_{mc}(\boldsymbol{r})$, is modeled as Gaussian noise with a variance σ^2 equal to twice the variance of the noise. A intensity difference $z_{\boldsymbol{r}}$ is assumed to correspond to noise (null hypothesis H_0) and not to the candidate blotch regions (hypothesis H_1) with the following probability:

$$p(z_{\boldsymbol{r}}|\mathrm{H}_0)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left\{-\frac{z_{\boldsymbol{r}}^2}{2\sigma^2}\right\}. \quad (8)$$

Under the assumption that neighboring pixels are statistically independent, the normalized square sum within a window $w_{\boldsymbol{r}}$ of size $N\times N$

$$\mathrm{T}_{\boldsymbol{r}}=\frac{1}{\sigma^2}\sum_{\boldsymbol{r}\in w_{\boldsymbol{r}}}z_{\boldsymbol{r}}^2 \quad (9)$$

is known to obey a χ^2 distribution with N^2 degrees of freedom. Thus the threshold $\mathrm{T}_{\boldsymbol{r}}$ can be determined from

$$\Pr(\mathrm{T}_{\boldsymbol{r}}>t_\alpha|\mathrm{H}_0)=\alpha_{sl} \quad (10)$$

where α_{sl} and t_α are a significance level and its corresponding threshold, respectively.

Whenever $\mathrm{T}_{\boldsymbol{r}}$ exceeds t_α, we decide a candidate BDM $Q(\boldsymbol{r})=1$, otherwise $Q(\boldsymbol{r})=0$. In this way, we can obtain the candidate forward and backward BDMs, Q_{forw} and Q_{back}, with respect to the adjacent frames.

The candidate BDMs present regions corresponding to the candidate region of the blotches in the current frame, if the motion estimator performs satisfactorily. Therefore, the maximization of the MAP problem is performed with respect to the pixels corresponding to $Q_{\text{forw}}(\boldsymbol{r}) = 1$ for the forward direction and $Q_{\text{back}}(\boldsymbol{r}) = 1$ for the backward direction. As a result, by means of restricting the blotch detection region to the candidate BDMs, our proposed method can drastically save the computational time for detecting blotches.

In practice, because the sequences being dealt with are degraded, it follows that the motion estimator suffers from the existing noises of degraded film sequences. Accordingly, the initial BDMs include the regions corresponding to the poorly motion estimated pixels. In the next step, therefore, we discuss the problem for falsely detecting the poorly motion-compensated pixels as blotches in the moving edge.

(Ⅲ) moving edge detection

In this step, we detect the moving edge field to avoid the confusion with the blotches caused by the poorly motion-compensated pixels. In order to find the pixels caused by being falsely estimated by motion vectors, we take advantage of the forward and backward motion-compensated frames. Under the assumption that there are no blotches in the two motion-compensated neighboring frames, we generate the moving edge field, E_{mef}, for the neighboring motion compensated frames using the significant test as stated above.

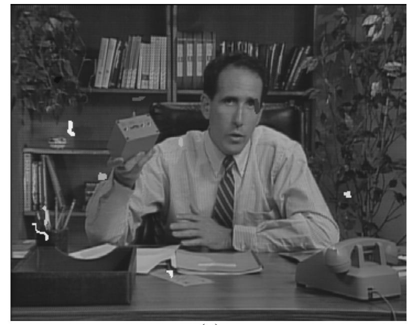
Whenever the moving edge field $E_{\text{mef}}(\boldsymbol{r}) = 1$, the weighting function of the *a priori* of Eq. (4) is defined as follows [4]:

$$\psi(\boldsymbol{r})=\begin{cases}\kappa \max\{CE(\boldsymbol{r})\}, & \sum CE(\boldsymbol{r}) < th_l \\ 0, & \text{otherwise}\end{cases} \tag{11}$$

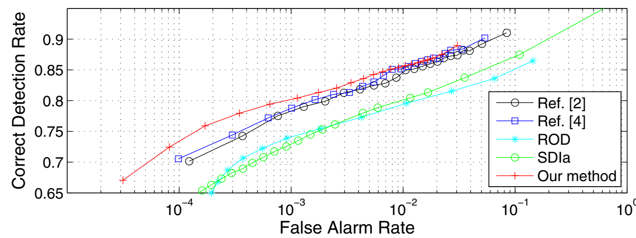
where κ and th_l denote a weighting constant and a threshold, and $CE(\boldsymbol{r})$ is defined as the set of four elements belong to the squared difference between two adjacent pixels in the horizontal, vertical, and two diagonal direction with respect to the centered pixel $\boldsymbol{r}$, respectively

(IV) Solution of the MAP problem

In this step, we discuss the solution of the MAP problem. The MAP problem for detecting blotches in Eq. (5) can be maximized using *simulated annealing* method using a logarithmic annealing schedule. It is maximized once with respect to the pixels corresponding to $Q_{\text{forw}}(\boldsymbol{r}) = 1$ for the forward direction and once with respect to the pixels corresponding to $Q_{\text{back}}(\boldsymbol{r}) = 1$ for the backward direction. The resulting blotch masks are combined by Eq. (1) to give the blotch detection mask $D(\boldsymbol{r})$. In our proposed method, after approximately $k = 50$ iterations, the algorithm is assumed to have converged.



(a)



(b)

Fig. 1. Results of detected blotch mask. (a)Artificially corrupted frame of sequence SALESMAN. (b) Performance of detectors applied to the salesman sequence.

4. EXPERIMENTAL RESULTS

To compare the efficiency of the proposed detector, we used the test sequence, "salesman", and the actual degraded film sequence, "Kanko Sendai". For the test sequence, a 288×360 subsection of the sequence was artificially corrupted with blotches of varying size and shape and random gray value [2], and to make the test sequence similar to real degraded film data, white Gaussian noise variance 10 was added after the blotches were added, as shown in Fig. 1(a). To compare the performance of the detectors, we use the Receiver Operating Characteristic (ROC) curve [1], and we have performed three blotch detection algorithms using MATLAB running on an Intel XEON 3.4 GHz machine with a Linux operating system.

In our experiment, the search space used for the full search block matching algorithm was ± 5 pixels. A block size of 8×8 was used. Based on the significance level $\alpha_{sl} = 10^{-2}$, we obtained a threshold of t_α for the square sum via a χ^2 distribution of $w_{\boldsymbol{r}} = 81$ of degrees of freedom in Eq. (10), and $\kappa = 0.03$ and $th_l = 50$ in Eq. (11). The parameters were found by setting $0.1 \le \alpha \le 2.0$, $\beta_1 = 30$ and $\beta_2 = 50$.

Figure 1(b) shows a plot of the correct detection rate versus false alarm rate for Ref. [2], Ref. [4] and our method, obtained from an average of 20 frames. The computation time required for detecting blotches per frame takes on average 10.26 s, whereas the computation time of Ref. [2] and Ref. [4] take on average 52.48s and 53.65 s, respectively, excepting the computation time of motion estimation. It is shown that although the correct detection rate is seen to be

Fig. 2. Frame from actual degraded sequence.

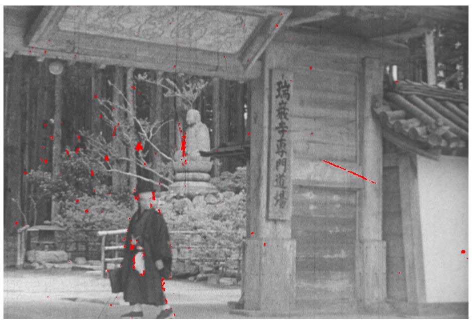


Fig. 3. Detection result using Ref. [2].

slightly smaller than that of the existing methods, our proposed method is superior to the existing methods for the false alarm rate. In addition, our proposed method give the lower computational time for detecting blotches.

The proposed method is applied for the blotch detection of an actual degraded film sequence. Figure 2 shows a frame of size 480×720 of the actual degraded film sequence,"Kanko Sendai". Figure 3– 5 show the results of the application of three detectors to the problem of detecting blotches in the actual degraded film sequence. Red indicates detected blotched pixels. The computation time required for detecting blotches per frame takes on average 77.05 s, whereas the computation time of Ref. [2] and Ref. [4] per frame take on average 173.09 and 181.19s, respectively, excepting the calculation time of motion estimation. It can be seen from the detection results that the false alarm rate of our proposed method is less than that of the existing method.In addition, the proposed method requires smaller computation time than the existing methods, because of restricting the attention of the process only to the candidate areas.

5. CONCLUSIONS

In this paper, we have proposed the blotch detection algorithm with quite low computational time and with low false alarm rate. The main idea is to restrict the attention of the detecting process only to the candidate distored areas being excluded if a discontinuity is not indicated. In addition, in order to avoid the bad influence due to the poorly estimated motion vectors, moving object edge detection has been incorporated in our proposed algorithm. The experimental results have shown a fast and efficient detecting performance of the proposed method compared with the existing MRF-based methods.

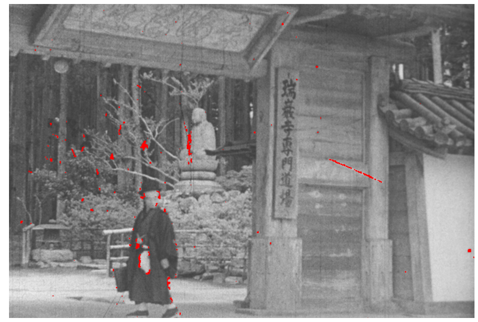


Fig. 4. Detection result using Ref. [4].

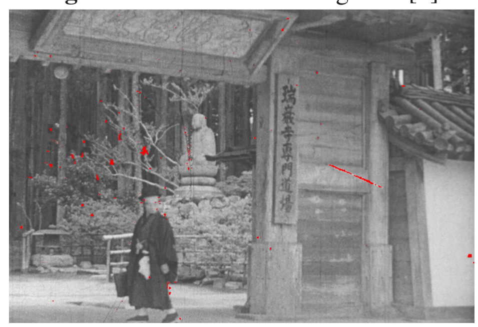


Fig. 5. Detection result using our method

6. REFERENCES

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