An Edge-Preserving MRF Model for the Detection of Missing Data in Image Sequences

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***Abstract*—This letter proposes a new spatial-temporal Markov random field (MRF) model for the detection of missing data (also referred to as blotches) in image sequences. The blotches in noise-corrupted image sequences exhibit a temporal discontinuity characteristic that is commonly used for the detection of blotches. However, badly motion-compensated pixels also appear as temporal discontinuities, making it difficult to distinguish the *true* blotches from the poorly motion-compensated regions. The proposed MRF model addresses the problem of incorrect detection due to poor motion compensation at the moving edges. It is found that the degree of incorrect detection (at the moving edges) in image sequences is reduced significantly by incorporating a moving-edge detector into the MRF model.**

***Index Terms*—Markov random field model, motion compensation, moving edge detector, restoration.**

I. Introduction

The typical artifacts in degraded motion picture material are bright and dark flashes, referred to as "dirt and sparkle" in motion picture industry. The successful treatment of these blotches of missing data in image sequences involves the motion compensation of the moving objects in the image sequence and accurate detection of these missing data [1] (hereby referred to as blotches) followed by the reconstruction [2] of the detected blotches. Some of the existing methods [1] for the detection of missing data in images sequences are i) spike detection index (SDI), ii) three-dimensional (3-D) autoregressive (AR) models, and iii) Markov random field (MRF) models. All these methods [1] require robust motion estimation algorithms to align the moving objects, without which the poorly motion-compensated pixels will be treated as temporal discontinuities and will therefore be confused with the blotches which also exhibit temporal discontinuity characteristic [3]. As a result, the moving regions that cannot be correctly motion compensated by the motion vectors will be falsely detected as blotches (temporal discontinuities) in the existing dirt and sparkle noise detectors [1]. The regions most susceptible to error in motion compensation are the moving edges, thus resulting in a soft-image after the restoration. In this work, we attempt to address this problem by formulating a new spatial-temporal MRF model to reduce the degree of false-alarm during the detection of the blotches.

The Baysian framework using an MRF prior [4] provides a convenient and consistent way of modeling context dependent entities such as image pixel intensities and other spatially correlated features. The detection of the blotches in image sequences is formulated as a *maximum a posteriori* (MAP) estimation problem that requires two probability distribution function (pdf) models: the conditional pdf of the observed image intensity and the *a priori* pdf of the blotches. The novel feature of our approach is the formulation of a new *a priori* function that is able to differentiate blotches from the temporal discontinuities due to poor motion estimation.

Manuscript received January 23, 1997. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. R. M. Mersereau.

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Publisher Item Identifier S 1070-9908(98)02844-2.

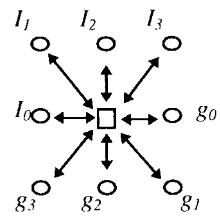

Fig. 1. Eight-pixel neighborhood for connected edge detection.

II. A New Spatio-Temporal MRF Model

Consider a finite lattice S that denotes the pixel lattice of two adjacent frames from a sequence, and $i(\vec{r})$ be the observed intensity at each site $\vec{r}$ of the lattice. Let $\Re$ denote the first-order neighborhood cliques [5] of site i. D denotes the blotch detection frame which is to be estimated using MAP formulation. Let $d(\vec{r})=1$ indicate the presence of a blotch at site $\vec{r}$ and $d(\vec{r})=0$ denote no blotch at site $\vec{r}$. I denotes the observed image frame with the intensity of each pixel, $i(\vec{r})$. Let $i(\vec{r}+\vec{v})$ denote the single motion-compensated neighbor pixel from the neighbor frame, where v denotes the motion vector which is computed using a multiresolution with full-search block matching algorithm [1]. The same likelihood function [1] is used in our model as follows:

$$P(I=i|D=d)=\frac{1}{Z_I}\exp\left[\frac{-1}{T}\sum_{\vec{r}\in S}\left(\alpha'\sum_{\vec{s}\in\Re_{\vec{r}}}(i(\vec{r})-i(\vec{s}))^2 + \alpha(1-d(\vec{r}))(i(\vec{r})-i(\vec{r}+\vec{v}))^2\right)\right]. \tag{1}$$

The prior model encourages the organization of the corrupted regions into connected regions:

$$P(D=d)=\frac{1}{Z_D}\exp\left(\frac{-1}{T}\sum_{\vec{r}\in S}[-(\beta_1 + \phi(i(\vec{r}),\vec{v}))f(d(\vec{r})) + (\beta_2+\phi(i(\vec{r}),\vec{v}))\delta(1-d(\vec{r}))]\right) \tag{2}$$

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where $f(d(\vec{r}))$ is the number of the four neighbors of $d(\vec{r})$ with the same value as $d(\vec{r}), \delta(\cdot)$ is the delta function, and function $\phi(i(\vec{r}), \vec{v})$ is a moving edge detector, which resolves moving edges in the frame currently being processed. $\phi(i(\vec{r}), \vec{v})$ is deterministically employed to locate moving edges before the prior model, (2) is formulated. Combining (1) and (2), the *a posteriori* distribution can be expressed as

$$\begin{aligned} P(D = d|I = i) &= P(D = d)P(I = i|D = d) \\ &= \frac{1}{Z}\exp\left(\frac{-1}{T}\sum_{\vec{r}\in S}[-(\beta_1 + \phi(i(\vec{r}), \vec{v}))f(d(\vec{r})) \right. \\ &\quad + (\beta_2 + \phi(i(\vec{r}), \vec{v}))\delta(1 - d(\vec{r}))] + \alpha(1 \\ &\quad \left. - d(\vec{r}))(i(\vec{r}) - i(\vec{r} + \vec{v}))^2]\right) \end{aligned} \tag{3}$$

where α, β_1, β_2 are the parameters used in the estimation. The term $\alpha' \ \Sigma_{\vec{s}\in\Re_{\vec{r}}} \ (i(\vec{r}) - i(\vec{s}))^2$ is dropped since it is not a function of d. The significance and setting of these parameters can be found in [1]. The MAP configuration of the detected frame is found by the optimization of the *a posteriori* distribution of (3). In this paper, simulated annealing is used for the optimization process.

III. Moving Edge Detector

To find the moving edges in image sequences, the connected edges are first obtained using a gradient operation, followed by a motion compensation process to distinguish the moving edges from the rest of the connected edges. In our implementation, the connected-edge is defined as any three neighboring pixels that exhibit a significant change in gradient as described in (4):

$$|I_m - g_m| > \tau_1 \quad \text{where } m = 0, 1, 2, 3 \tag{4}$$

where τ_1 is a threshold set to optimistically include all edges. τ_1 is set to 25 in our implementation. I_m and g_m are a pair of pixels as shown in Fig. 1. The gradient of the central pixel under consideration (see Fig. 1) is computed together with the gradients of its neighboring pixels. If two or more gradients are found along with the gradient of the central pixel, the central pixel is then flagged as a connected edge; all the gradients must satisfy (4). The resulting connected edge field comprises both the moving-edges and blotch-edges. To distinguish the two, the bidirectional displacement frame difference (DFD) of each of the neighbors in the connected-edge field are examined. The criterion for flagging the central pixel under consideration as a moving edge is set as follows:

$$\begin{aligned} &|i(\vec{r} + \vec{v}_f, n - 1) - i(\vec{r}, n)| \\ &\quad < \tau_2 || |i(\vec{r} + \vec{v}_b, n + 1) - i(\vec{r}, n)| < \tau_2 \end{aligned} \tag{5}$$

where $||$ is a logical OR operation; $i(\vec{r})$ represents a neighborhood pixel; $i(\vec{r}+\vec{v}_f, n-1)$ represents its motion-compensated pixel in the previous frame; and $i(\vec{r}+\vec{v}_b, n+1)$ represents its motion-compensated pixel in the next frame. Bidirectionality is used to account for the occluded or uncovered areas. This criterion is optimally set to allow the detection of blotch edges in our MRF model. In our implementation, τ_2 is chosen (heuristic) to be ten. The *a priori* model is weighted proportional to the strength of the largest gradient $(I_{m'}, g_{m'})$ across the moving-edge

$$\begin{aligned} \phi(i(\vec{r}), \vec{v}) = k \cdot (I_{m'} - g_{m'})^2/\tau_1^2 \quad \text{where} \\ (I_{m'} - g_{m'})^2 = \max\{(I_m - g_m)^2, m = 0, 1, 2, 3\} \end{aligned} \tag{6}$$

where k is a constant set to 30 for the moving edges, otherwise k is set to zero. This new moving-edge detector avoids the problems of false alarms at moving-edges by lowering the emphasis of the likelihood model described in (1). Although using three frames for detection can reduce the problems caused by occlusion and uncovering of objects [1], poor estimate in the vicinity of the moving edges is still a problem to be solved in the existing blotch detection algorithms. The moving edge detector $\phi(i(\vec{r}), \vec{v})$ can be seen as a weighting function to alleviate the false detection of the temporal discontinuity that is due to poor motion estimate; the prior pdf will be weighted more than the likelihood function when a moving-edge is found.

IV. Results and Performance Analysis

Two test image sequences—the salesman sequence with artificially added blotches [1] of variance between 5–10 gray levels and one real image sequence—are used in our experiments. Two parameters—percentage of correct detection (of the blotches) $\%C$, and the percentage of false alarm $\%F$ [1]—are used to evaluate and compare the performance. Fig. 2 shows a plot of the correct detection rate versus false alarm rate, for the three detectors: proposed MRF model, Kokaram *et al.* MRF model, and the bidirectional SDI detector [1]. The results presented in Fig. 2 are obtained from an average of ten frames per image sequence with the motion vectors obtained from the degraded sequences. The MRF detectors' characteristics were found by setting $\beta_1 = \beta_2 = 30$ and $0.25 \le \alpha \le 3.0$. It can be seen that the proposed MRF model performs very well in general, and out performs the previously reported detectors. The slight drop $(\sim 1\%)$ in correct detection is trivial (1% corresponds to only about five pixels in a frame) whereas the reduction of the number of false alarm pixels is of the order of hundreds of pixels (1% corresponds to 655 pixels in a 256 $\times$ 256 pixels frame). Fig. 3(a) shows an image obtained from an old movie archive. The blotches are being detected using the proposed algorithm and depicted in Fig. 3(b). Fig. 3(c) shows the detected blotches using Kokaram *et al.* MRF model [1]. It can be seen from Fig. 3(b) and (c) that the false alarms along the moving-edges are reduced in the newly proposed MRF model. Fig. 3(d) depicts the region being detected as moving-edges (in gray) and the region being detected as blotch-edges (in black). Comparing Fig. 3(a) and (d), it can been seen that the moving-edge detector has quite successfully identified the blotch-edges from the moving edges, thus resulting in a lower false alarm rate in the newly proposed MRF model.

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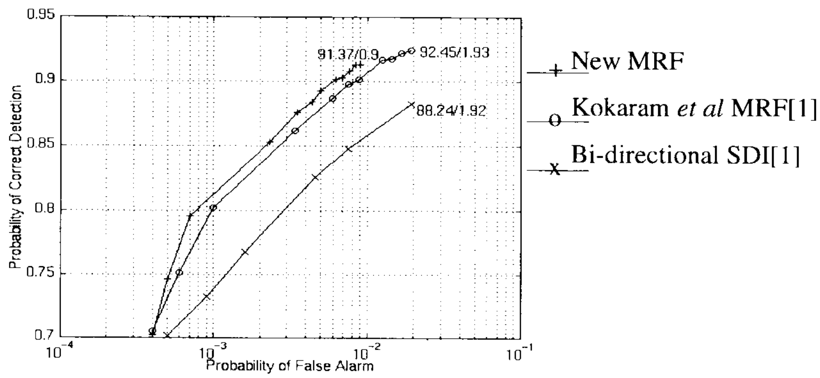

Fig. 2. Performance of detectors of the salesman sequence.

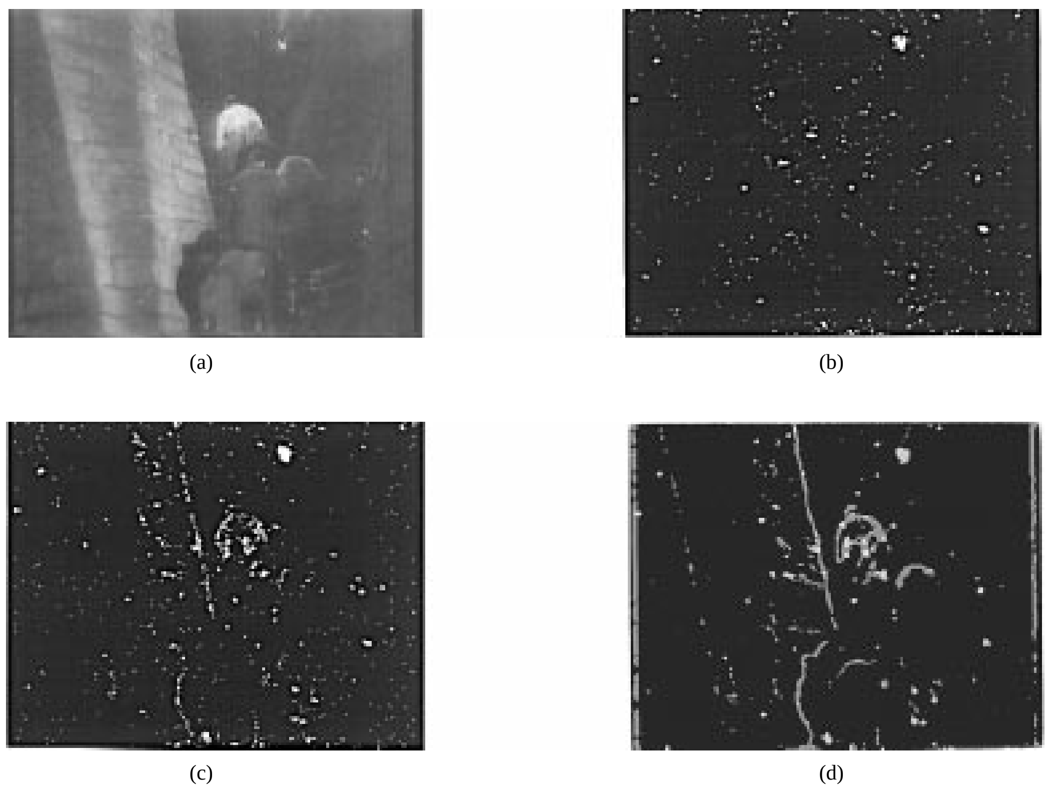

Fig. 3. (a) Sample of an old movie archive. (b) Detected blotches using the proposed MRF model. (c) Detected blotches using Kokaram *et al.* MRF detector. (d) Detected fields of moving-edges (in gray) and blotch-edges (in black).

V. Conclusions

It has been found that the success of a blotch detector depends on the accuracy the motion estimates. In practice, one could improve the accuracy of the blotch detector by reducing the bad influence of the motion estimates in the detection algorithm. This work improves the performance of the MRF detector [1] further by reducing the influence of the motion estimates at the moving edges since small errors in motion estimates tend to result in large temporal discontinuities in region of sharp edges. The proposed MRF detector yields a more accurate and efficient video restoration algorithm [6], which will only repair the blotched pixels without disturbing the edges of the image.

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