A NEW SPATIO-TEMPORAL MRF MODEL FOR THE DETECTION OF MISSING DATA IN IMAGE SEQUENCES

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ABSTRACT

This paper proposes a new spatial-temporal MRF model for the detection of missing data (also referred to as blotches) in image sequences. The blotches in noise-corrupted image sequences exhibit temporal discontinuity characteristic which is commonly used for the detection of blotches. However, the badly motion compensated pixels will also appear as temporal discontinuities, thus making it difficult to distinguish the *true* blotches from the poorly motion compensated regions. The proposed MRF model addresses the problem of incorrect detection. It is found that the degree of false-alarm in the detection of the blotches in image sequences can be reduced by using a moving-edge detector in the MRF model to identify the blotch-edges from the moving-edges.

1. INTRODUCTION

Restoration of degraded motion pictures is a highly labour-intensive and extremely costly undertaking. A much publicised event[1] is the restoration work of Disney's 1937 masterpiece - *Snow White and the Seven Dwarfs*, which was re-released in digital form in 1993. A motion picture restoration system which can automatically remove artefacts in film archives will be of great interest to the entertainment and broadcast industry. The typical artefacts 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 three processes: motion compensation of the moving objects in the image sequence, accurate detection of these missing-data[2] hereby referred to as blotches, and follow by the reconstruction of the detected blotches using either spatio-temporal filters[3], interpolation techniques [4] or Markov Random Field (MRF) model-based approach [4, 5].

Some of the existing methods[2] for the detection of missing data in images sequences are: Spike Detection Index (SDI) method, 3D auto-regressive model (AR) and MRF model. All these methods[2] require robust motion estimation algorithm to motion compensate the moving objects in image sequences, otherwise the badly motion compensated pixels will be treated as temporal discontinuities and will therefore be confused with the blotches which also exhibit temporal discontinuity characteristic[6]. It is not always practical to employ pixel (or sub-pixel) accurate motion estimation algorithm due to the enormous amount of computational cost incurred and the very large amount of data involved in restoring a motion picture. A multiresolution motion estimation scheme using full-search block matching algorithm[2] is used here for the purpose of motion picture restoration. However, none of the block matching algorithms could yield motion vectors that perfectly and completely describe the motion in image sequences, not to mention the poor performance of the motion estimation algorithms due to the presence of noise in old motion pictures. As a result, the moving regions that cannot be correctly motion compensated by the (estimated) motion vectors will be falsely detected as blotches (temporal discontinuities) in the existing 'dirt & sparkle' noise detectors[2]. The degree of incorrect detection is measured and referred to as *false-alarm* in Kokaram's paper[2]. In this paper, we attempt to address this problem by formulating a new spatial-temporal MRF model for more accurate detection of noise in corrupted motion pictures.

Maximum A Posteriori (MAP) probability and Markov Random Field (MRF) theory[7] provide a convenient and consistent way of modelling 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 MAP estimation problem which requires two pdf models: the conditional pdf of the observed image intensity given the blotches, called the likelihood model, and the *a priori* pdf of the blotches which we attempt to model. The novel feature of our approach is the formulation of a new *a priori* function which is able to differentiate blotches from the temporal discontinuities due to poor motion estimation, thus reducing the degree of false-alarm in the blotch detection algorithm.

2. A NEW SPATIO-TEMPORAL MRF MODEL

Consider a finite lattice S which 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 (same as Geman's definition [5] of first-order neighbourhood cliques) spatial neighbourhood of site i. Define a discontinuity frame, D which denotes the blotch detection frame which is to be estimated using MAP formulation. Let

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$d(\vec{r}) = 1$ indicate the presence of a blotch at position $\vec{r}$ and $d(\vec{r}) = 0$ denote no blotch at position $\vec{r}$. I denotes the observed image frame with the intensity of each pixel, $i(\vec{r})$. Let $i(\vec{v})$ denote the single motion-compensated neighbour pixel from the neighbour frame.

The same likelihood function as described in [2] is used in our model as follows:

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

To compute the motion vector, $\vec{v}$ of the proposed model, a multi-resolution with full-search block matching algorithm is used.

The prior model encourages the organisation of the corrupted regions as connected regions, and is given as follows:

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

Where $f(d(\vec{r}))$ is the number of the four neighbours of $d(\vec{r})$ with the same value as $d(\vec{r})$, $\delta(.)$ is the delta function, and function $\phi(i(\vec{r}),\vec{v})$ is a moving edge detector between frames. The novel moving edge detector is employed in the model to reduce the degree of false-alarm during the detection process. A moving edge detector function is added to weight the *a priori* model of the distribution. However, this weight is dependent on the gradient of the edge of the pixels under consideration. This follows from the observation that small errors in motion estimates tend to result in larger temporal discontinuities in regions of sharp edges. Hence, the detection field of these pixels cannot be equally emphasized by the likelihood model (temporal discontinuity) as that would almost always lead to them being flagged as blotched. The effect of this moving edge detector function $\phi(i(\vec{r}),\vec{v})$ will be apparent by examining the *a posteriori* distribution as shown in equation (3).

Having formulated (estimated) the prior distribution and the likelihood function of the corrupted regions, optimal results could be estimated from these sources of knowledge by using Bayes' criterion. Combining equations (1) and (2), the *a posteriori* distribution can be expressed as:

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

α, β_1, β_2 are the adjustable parameters used in the estimation. The significance and setting of these parameters can be found in [2]. $\phi(i(\vec{r}),\vec{v})$ is included in the *a posteriori* distribution because of the strong dependence of the likelihood function on the motion vector estimate. The poorly motion compensated regions will appear as temporal discontinuities and will be confused with the ***true*** temporal discontinuities (i.e. blotches), hence the likelihood function is error-prone in image regions which undergo non-translational displacement. Although using three frames for detection can reduce the problems caused by occlusion and uncovering of objects[2], 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 function $\phi(i(\vec{r}),\vec{v})$ 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.

To find the MAP configuration of the detected frame, given the image and the model for the missing regions, a number of optimisation methods[7] such as Simulated Annealing (SA), Iterated Conditional Modes (ICM), genetic algorithm, and Mean Field Annealing could be used. In this paper, SA is used in the optimisation process.

3. MOVING EDGE DETECTOR

The moving edge detector, $\phi(i(\vec{r}),\vec{v})$ uses a moving edge detector to overcome the problem of false alarms at moving edges. This is essentially due to poor motion estimation at moving edges. The moving edge detector consists of two steps: a *connected-edge detector* and a *moving-edge detector*. The entire algorithm is formulated as follows :

(I) First, connected-edge detection is performed for each pixel. The connected edge detector determines whether a pixel lies on an edge that is connected with two other edge pixels, which lie in the 8-pixel neighborhood as shown in figure 1. The central pixel is the one for which connected-edge detection is being done. The connected-edge detector works as follows :

(Ia)Gradients are calculated along the 4 *pairs* of neighborhood pixels, (I_n, g_n) as shown in figure 1. A (possible) connected-edge is flagged if :

$$|I_n - g_n| > \tau_1 \quad \text{where } n=0,1,2,3 \quad (4)$$

where τ_1 is a threshold set to optimistically include edges. (A value of around 25 has been experimentally found to yield optimal results). I_n and g_n represents the two pixels forming a pair.

(Ib)In our implementation, the connected-edge is defined as any 3-neighbour pixel that exhibits a significant change in gradient as described in equation (4). The gradient of the remaining 6 neighboring pixels (other than the gradient pair (I_0, g_0), must be examined using equation (4). If the

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gradients are found on 2 of these 6 neighbors, the central pixel is then flagged as a connected edge. There are therefore 3 pixels lying on an edge.

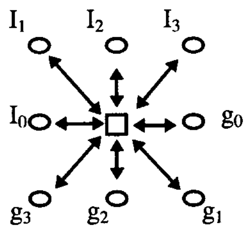

Figure 1. 8-Pixel Neighborhood For Connected Edge Detection

(II) The connected-edge field found from step (I) above comprises both the moving-edges and blotch-edges. Hence, the connected-edge field is passed through a moving-edge detector, which detects the *moving-edges* based on the temporal discontinuity property of a blotch. Consider an example depicted in figure 2. 'ce' represents pixels flagged as connected edges. The central 'ce' pixel is the one under consideration now. 'b' represents pixels lying in the interior of the blotch. 'nb' are pixels lying outside the blotch. Figure 2a demonstrates the case of a blotch edge whereas figure 2b shows a moving-edge.

nb	**ce**	**b**		**nb**	**ce**	**nb**
nb	**ce**	**b**		**nb**	**ce**	**nb**
nb	**ce**	**b**		**nb**	**ce**	**nb**
	(a)				(b)	

Figure 2. Blotch Edge Detection

Now, by the definition of a blotch, the 'b' pixels will have a large motion-compensated temporal difference in both the succeeding and preceding frames (3 frames are taken into consideration). A moving-edge, on the other hand, will have well-compensated pixels in the region around it, since it will be surrounded by more or less homogenous, non-blotched areas in its neighborhood. The pixel is therefore flagged as a moving-edge if equation (5) is satisfied for all the neighboring pixels, excluding the 'ce' pixel.

$$|I(i + dx_1 + dy_1, n-1) - I(i, n)| < \tau_2 \quad \text{OR}$$
$$|I(i + dx_2 + dy_2, n+1) - I(i, n)| < \tau_2 \qquad (5)$$

Here $I(i, n)$ represents the neighborhood pixel, $I(i + dx_1 + dy_1, n-1)$ represents its motion compensated pixel in the previous frame and $I(i + dx_2 + dy_2, n+1)$ represents its motion compensated pixel in the next frame. Bi-directionality is used to account for the occluded or uncovered areas.

(III) At the end of step (II), the entire image has been split into two logical regions: non-moving and moving edges. The *a priori* model is weighted proportional to the strength of the gradient across the moving-edges:

$$\phi(i(\vec{r}), \vec{v}) = \psi.(I_0 - g_0)^2 / \tau_1^2 \qquad (6)$$

where ψ is a constant set to 90; for non-moving edge, ψ defaults to zero.

This new moving-edge detector avoids the problems of false alarms at moving-edges by lowering the emphasis of the likelihood model as described in equation (2).

4. RESULTS AND PERFORMANCE ANALYSIS

Three test image sequences: 2 image sequences with artificially added blotches and 1 real image sequence (obtained from an old movie archive) are used in our experiments. On both the synthetic sequences, the blotches were added onto the frames using a Gibbs sampler employing Ising's model[8]. The blotch pixels are given a variance between 5 to 10 grey-levels, which are closer to the characteristic of the real blotches found in old movie archives. The results of our proposed model is compared and evaluated with Morris' MRF model as presented in [2]. Two parameters: percentage of correct detection, %C (of the blotches), and the percentage of false detection, %F (which is also referred to as false alarm in [2]) are used to evaluate and compare the performance. The robustness of the proposed algorithm is demonstrated through the blotch detection examples in different image sequences such as the Salesman sequence and the Western sequence as presented in [2]. The results are obtained from an average of 10 frames per image sequence. The results are tabulated and shown in Table 1. It can be seen that with the new MRF model, the false-alarm is reduced significantly whereas the number of correctly detected pixels is almost the same as Morris' model. By using Morris's parameters (α, $\beta_1+\psi$, $\beta_2+\psi$) indiscriminately without using the moving-edge detector (see Table 1 second row of entries), although the false-alarm is reduced, the number of correctly detected pixels falls as well.

Figure 3a shows an image obtained from an old movie archive. The blotches are being detected using the proposed algorithm and depicted in figure 3b. Figure 3c shows the detected blotches using Morris' MRF model as reported in [2]. It can be seen from figures 3b and 3c that the false alarm along the moving-edges is reduced in the newly proposed MRF model.

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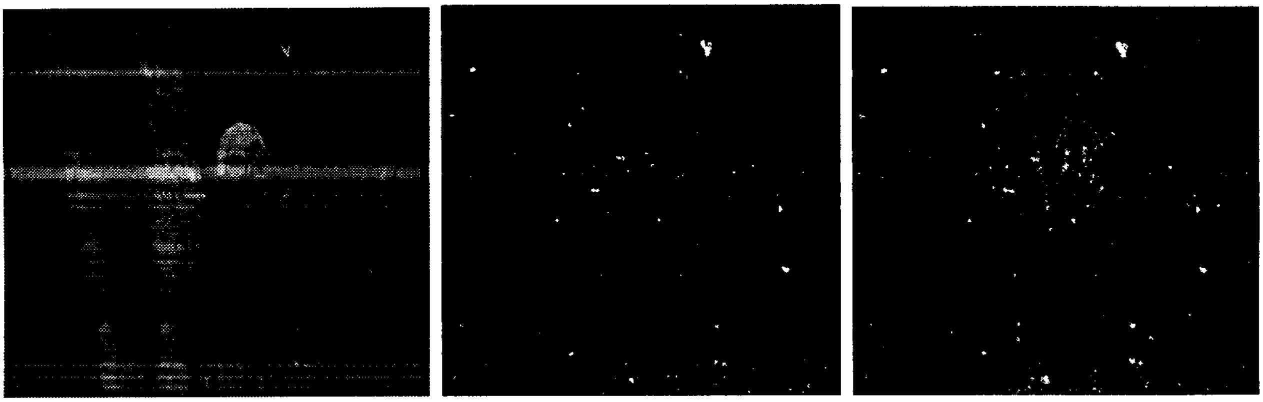

(a) (b) (c)

Figure 3 (a) A sample of an old movie archive (b) The detected blotches using the proposed MRF model
(c) The detected blotches using Morris' MRF detector

	Detection Algorithm	Salesman		Western	
		%C	%F	%C	%F
1	Morris model [2,8] (parameters α=2 , β_1= 30, β_2= 30)	91.70 (444)	1.26 (825)	93.25 (426)	0.59 (386)
2	Morris model [2,8] (parameters α=2 , β_1=120 , β_2=120)	80.14 (388)	0.10 (65)	84.85 (387)	0.08 (52)
3	New MRF Model (parameters α=2 , β_1=30,β_2=30, ψ=90)	89.41 (433)	0.52 (340)	91.94 (421)	0.33 (216)

Note: The entries in parentheses denote the absolute number of pixels detected/incorrectly detected;. %C=[(no. of pixels detected)/(total no. of blotch pixels)] x *100% ; %F=[(no. of incorrectly detected pixels)/(total no of pixels in a frame)]* x *100%*

Table 1. Correct Detection/False Alarms Performance between Morris MRF Model and the new MRF model

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