A MRF Model Based Scheme for Accurate Detection and Adaptive Interpolation of Missing Data in Highly Corrupted Image Sequences

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Abstract

This paper proposes a robust spatial-temporal MRF model based scheme for aggressive detection and accurate interpolation of missing data (blotches) in highly corrupted image sequences. The blotches in noise-corrupted image sequences exhibit a temporal discontinuity characteristic, which is used for the detection of blotches. The MRF model addresses the problem of incorrect detection due to poor motion compensation at moving edges, by incorporating a moving-edge detector into a priori model. In highly corrupted image sequences where an aggressive detector is needed, the detection field can be interpreted as three main classes. This classification allows for effective noise-removal. These regions are blotches that are to be interpolated: (a) with the existing motion vector field, (b) requiring motion vector correction, and other (c) falsely detected regions. This results in a novel scheme that effectively subdues noise without corrupting other areas of heavily distorted image sequences.

1. Introduction

The typical artefacts found in highly degraded motion picture material are bright and dark flashes of varying sizes, 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, accurate detection of these missing-data [1, 2], hereby referred to as blotches, and followed by the effective reconstruction [6] of the detected blotches. All detection methods [2] 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 [2]. For effective restoration of highly corrupted image sequences an aggressive detector is required to detect all the distorted areas.

However an aggressive detector will cause an increase in false alarms, therefore a classification scheme has been developed to allow for effective interpolation of this heavy detection field. The detection field is classified into the three following classes: (a) those detected areas that are to be interpolated with the existing motion vector field; (b) detected areas that require motion vector correction and, (c) other detected areas that have most probably been "falsely detected".

Detected regions that fall into class (b) are blotches that might not have motion vectors estimated properly below them due to the heavily corrupted nature of the image sequence (especially large blotches). Detected regions that fall into class (c) are those that refer to regions of missing data that have been falsely detected due to the aggressive nature of the detector, especially at moving edges.

2. Spatio-Temporal MRF Detection 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 neighbourhood cliques [5] of site i. D denotes the blotch detection frame, which is to be estimated using a 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 neighbour pixel from the neighbour frame, where $\vec{v}$ denotes the motion vector which is computed using a bi-directional multi-

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resolution with a full-search block matching algorithm at each resolution [4]. The same likelihood function [2] is used in our model as follows:

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

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

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

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, 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, equation (2) is formulated. Combining equations (1) and (2), the *a posteriori* distribution can be expressed as:

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

where α, β_1, β_2 are the parameters used in the estimation. In this paper, Simulated Annealing is used for the optimisation process.

For aggressive detection, in the case of heavily corrupted image sequences, the value of α was set to high values, thereby giving the temporal component in (3), greater weight.

To find the moving edges in image sequences [1], 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. This moving-edge detector avoids the problems of false alarms at moving-edges by lowering the emphasis of the likelihood model described in equation (1).

The moving edge detector $\phi(i(\vec{r}),\vec{v})$; is based on a function of the neighbouring pixels $i(\vec{r})$, and their motion compensates $\vec{v}$. It can be seen as a weighting function to help alleviate the false detection of the temporal discontinuity that is due to poor motion estimate. In equation (3) the prior pdf will be weighted more than the likelihood function when a moving-edge is found.

3. Classification Scheme

The classification scheme described here aims to strike a balance between effective noise removal and making sure that no artefacts are generated during the restoration of heavily corrupted image sequences. The algorithm attempts to exploit as much information as we possess about the distorted image sequence. The interpolation algorithm adapts to properties of the image sequence. The correctness of the motion vectors required for accurate interpolation of missing data is very important.

The classification scheme is outlined below in the steps (a) - (e):

a) The first step in the classification scheme is to do a connected region operation on the heavy MRF detection field $d(\vec{r})$, obtained from detection algorithm. Each connected region is operated on independently. Each connected region, $\wp$, after it is identified has some statistical properties computed that will help carry out the classification for effective interpolation.

b) The mean intensity $\mu_\wp$ of the detected connected region, $\wp$, is first computed as:

$$\mu_\wp = \Sigma\Sigma\, I(x, y)/N \tag{4}$$

where $I(x, y)$ are pixels present in the connected region , $\wp$, and N is the total number of pixels in the region.

c) **"False Detection" classification**: Connected regions are flagged to be falsely detected (no interpolation is carried out) if any of the two following two criteria are met:

(i) The mean intensity $\lambda_\wp$ of the non-detected regions in a two-pixel neighborhood (as shown in Figure 1) around the blotch $\wp$, is computed as in:

$$\lambda_\wp = \Sigma\Sigma\, I(x, y)/N \tag{5}$$

where $I(x, y)$ are pixels in the neighborhood of the connected region and N is the total number of pixels in the neighboring area. If (6) is found to be

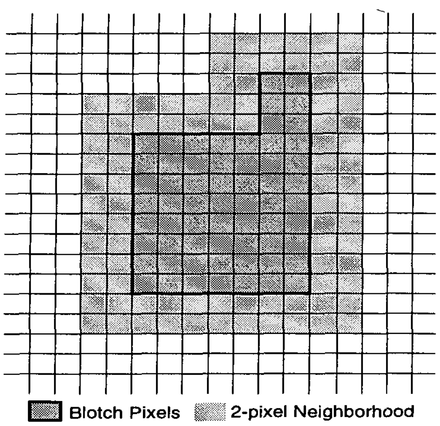

Figure 1: Blotch and its 2-pixel connected neighborhood (step c(i))

true then the connected region is classified as "falsely detected".

$$|\mu_{\wp} - \lambda_{\wp}| < t_0 \qquad (6)$$

(ii) If greater than X percent of pixels, of a 2-clique (N_2) neighborhood, R_2, of the blotch, $\wp$, when compared to corresponding pixels of a 2-pixel region, R_1, at the edge of the blotch, $\wp$ (as shown in Figure 2) are less than a certain threshold (t_1) (equation (7)). Then the whole blotch region is also classified as "falsely detected".

$$\begin{aligned} &\sum_{i\in R_1} f(x_i) > X \times \sum_{i\in R_1} N(i) \\ &f(x_i) = \sum t(x_i, x_j), \quad j \in R_2, j \in N_2(i) \\ &t(x_i, x_j) = \begin{cases} 1 & if \quad |x_i - x_j| < t_1 \\ 0 & else \end{cases} \\ &N(i) = \sum_{j\in R_2, j\in N_2(i)} 1 \end{aligned} \qquad (7)$$

This follows the reasoning that such areas are either extremely faint noise or are falsely detected portions. They could be poorly motion compensated areas in the image or could be regions of fast or blurred motion.

d) **"Vector Correction" classification**: The mean absolute difference's (MAD) of the connected blotch $\wp$, in both the backward and forward motion compensated frames are computed as (8):

$$\begin{aligned} MAD_b &= \sum\sum |I(x,y) - I_b(x + \vec{v}_{bx}, y + \vec{v}_{by})| / N \\ MAD_f &= \sum\sum |I(x,y) - I_f(x + \vec{v}_{fx}, y + \vec{v}_{fy})| / N \\ &(MAD_f \ \& \ MAD_b) > t_2 \end{aligned} \qquad (8)$$

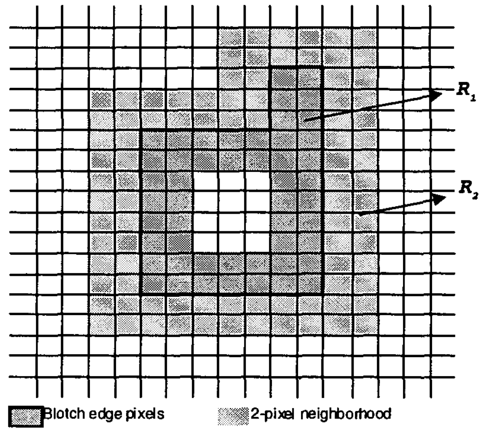

Figure 2: Blotch edge pixels and its 2-pixel neighborhood for step (c(ii)

If the differences, MAD_f and MAD_b are both greater than t_2 (7), then the region is classified to be motion vector corrected before interpolation (N is the number of pixels in the connected blotch, the subscripts b and f refer to backwards and forwards respectively, $\vec{v}$ to the motion vector). The motion vector correction is carried out using a MRF motion vector prior scheme as in [3], before it is interpolated using a 3-D auto-regressive model (AR) as in [6]. All such single connected regions are interpolated from a single temporal direction (i.e. backwards or forwards) to allow for better textural fidelity of the interpolated regions.

e) **Normal classification**: The rest of the pixels that are not classified as "falsely detected" or flagged for "vector correction" are classified for normal restoration. The interpolation is carried out as in [6] with the existing set of motion vectors, that the detection was carried out with.

In experiments conducted, the values of the following unknown variables were heuristically selected; X was set to 50%, t_0 to 5, t_1 to 5 and t_2 to 20.

4. Results

Results have been obtained using a real image sequence, EASTERN (PAL resolution, 576×720), which is heavily corrupted with noise. Figure 3(a) shows an original frame from the image sequence. Figure 3(c) shows the resultant image frame after running the motion estimation; detection; classification and interpolation algorithms as have been described in the previous two sections.

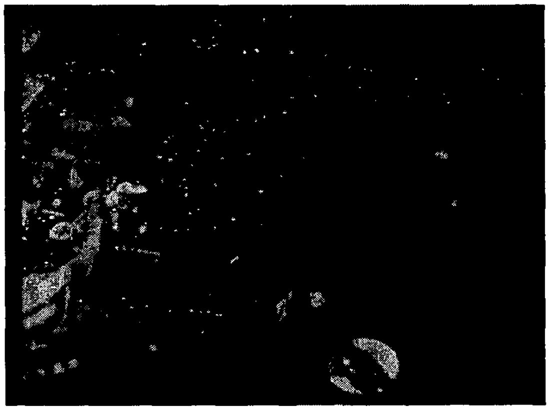

Figure 3(a): Original heavily degraded frame from the EASTERN image sequence

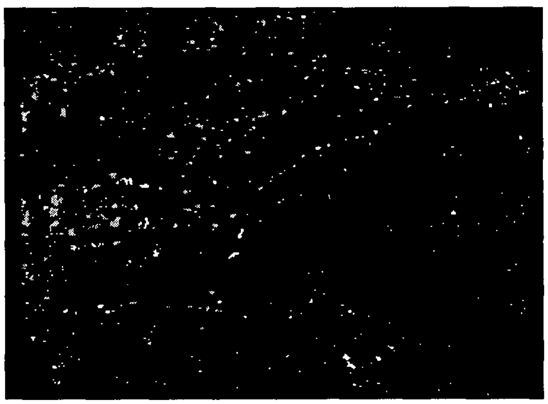

Figure 3(b): Detection-classification map of the frame in Figure 3(a)

Figure 3(c): Restored version of the frame in Figure 3(a)

Figure 3(b) shows the detection classification map; divided into three classes (*the black areas are those that are not detected*). The (i) darkest shaded regions show the detected areas that have been classified as being "falsely detected" (steps *c(i)* and *c(ii)*, section 3). The (ii) white regions have been interpolated normally without any motion vector correction (step *e*, section 3) [6]. The (iii) rest (lightly shaded regions) have been interpolated [6] after motion vector correction as employed (step *d*, section 3) as in [3].

It can be seen from Figure 3 that errors at falsely detected areas such as the plate (lower right corner of the image), are avoided due to its being classified as a region that has been "falsely detected".

5. Conclusions

In this paper we have presented a scheme for restoration of sequences that are heavily degraded. The scheme tries to aggressively subdue noise and at the same time not introduce any artifacts into the image sequence. In this paper we have presented some preliminary results of employing a classification scheme to adaptively switch between different types of interpolation schemes, depending on the reliability of the motion vectors computed and the image sequence information available.

For future research, classification schemes could carry out a more detailed study and characterization of the motion vectors obtained from heavily corrupted image sequences.

6. References

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