

## High Performance Missing Data Detection and Interpolation for Video Compression and Restoration Applications

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## Error Concealment in Wireless Transmission

– During wireless transmissions packet loss can occur; some measurements report averages of about 3.6% of packet loss.

– Typical techniques are Forward Error Correction (FEC) and Automatic Retransmission Query (ARQ), which require extra error correction packets to be transmitted.

– Other approaches include the use of available information carried out by surrounding blocks or by nearby motion compensated frames



## Digital film restoration



- Digital material is typically degraded due to physical problems in repeated projection or playback or simply the chemical decomposition of the original material.
- Typical problems: noise, dirt and scratches due to dust or abrasion.
- Manual retouching is highly required and automatic batch processing is limited to low degraded video sections (e.g. speckle noise, brightness variation)

## Characteristic of Blotchy Noise

- Blotches hardly ever occur at the same spatial location in successive frames;
- The intensity of a blotch is significantly different from its neighbouring uncorrupted intensities;
- Blotches form coherent regions in a frame;
- They might **NOT**:
  - Be purely black/white
  - Have clear border



Possible causes:

- Dirt particles covering film
- Mishandling or aging of film
- Signal lossing due to transmission

## Problems & Challenges

- Huge amount of data
  - Restrict computational complexity
  - Automatic processing preferred
- Motion estimation tricked by :
  - Presence of noise
  - Illumination Change
  - Blurry scene for fast motion
  - ...
- Automatic detection not easy
  - Blotchy noise not readily modeled
  - Decision rely on motion compensated results

## High performance computing

- A great improvement in this field should be related to the development of high performance software
  - to optimize the response time, too high to adopt the restoration algorithms in interactive modality
    - e.g. recent digital restoration of the movie, named Rory O'More and produced by Sydney Olcott in 1911, has taken 134 hours.
    - usual request is 0.1-0.2 fps
  - to allow the use of highly specialized algorithms in order to ensure (possibly) automatic or semi-automatic restoration of degraded video of great quality.

## Blotch detection

$$b(x,y,t) = \begin{cases} 1 & \text{if } (x,y,t) \in \Omega \\ 0 & \text{if } (x,y,t) \in D - \Omega \end{cases}$$

Blotch domain

$\Omega$



Degraded image

$$Z(x,y,t) = (1-b(x,y,t)) I(x,y,t) + b(x,y,t) c(x,y,t)$$

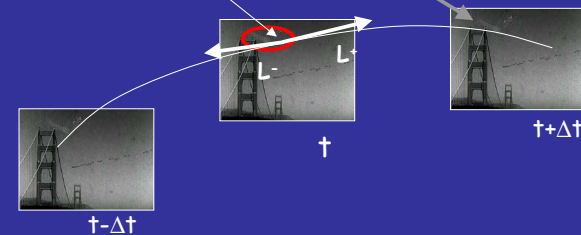
$\sigma^2(c) < \epsilon$ : the variance of  $c$  is small

## Blotch detection

Blotch domain (connected):

$\Omega$

Motion trajectory



$$\left| \frac{dI}{dL^+} \right| > k$$

$$\left| \frac{dI}{dL^-} \right| > k$$

For all points  $(x,y,t)$  in  $\Omega$ , the **directional derivatives** of  $I(x,y,t)$  computed along the motion trajectory across the two different directions  $L^+(t \rightarrow t+\Delta t)$  and  $L^-(t \rightarrow t-\Delta t)$  **are large**

## Blotch Removal

- Inpainting = **Image Interpolation**.

(initially circulated among museum restoration artists; first introduced into I.P. by Sapiro's group [EECS, UMN, 1999] )

- What makes inpainting difficult is the complexity of images:

- having a large dynamic range of **scales**;
- intrinsically non-smooth due to **edges and boundaries**;
- the missing domains can have **complicated topology**;
  
- direct classical interpolation tools perform less ideally:
  - polynomials (Lagrange, Hermite, splines);
  - linear filtering (Fourier, wavelets, linear (heat) diffusion);
  - radially symmetric functions (as in spatial statistics).

## Degraded Video Restoration

- The general scheme is:

$$I^{n+1}(\mathbf{x}) \leftarrow I^n(\mathbf{x}) + \alpha \Pr(b(\mathbf{x}) = 1) \cdot CT$$

where  $b(\cdot)$  is the *blotch mask*,  $\alpha$  is a rate parameter and CT a Correction Term.

- Our choices:

- Blotch Detection
  - **Hard thresholding** of  $\Pr(b(\mathbf{x})=1)$ : **Spike Detector Index (SDI)**
- Blotch Removal
  - Spatio-temporal extension of **the reaction-diffusion method** for texture disocclusion (parameters  $\alpha$  and CT) (*Acton et al., IEEE TIP, 2001*)

## Blotch detection method

- Motion estimation

- Spike detection index (SDI)

– Initialize  $b(\mathbf{x})$  field:

$$b(\mathbf{x}) = \begin{cases} 1 & \text{if } (|\Delta_f| > T_1) \text{ AND } (|\Delta_b| > T_1) \\ & \text{AND } ((\text{sign}(\Delta_f) - \text{sign}(\Delta_b)) < T_2) \\ 0 & \text{otherwise} \end{cases}$$

– backward motion compensated frame difference  $\Delta_b = I_t(\mathbf{x}) - I_{t-1}(\mathbf{x} + \mathbf{d}_{t,t-1}(\mathbf{x}))$

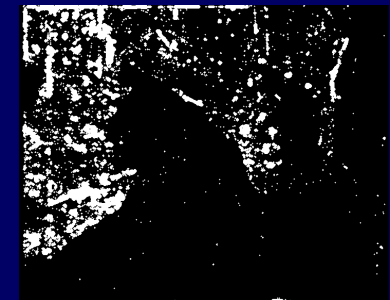
– forward motion compensated frame difference  $\Delta_f = I_t(\mathbf{x}) - I_{t+1}(\mathbf{x} + \mathbf{d}_{t,t+1}(\mathbf{x}))$

The SDI simply flag a pixel as corrupted when both the forward and backward motion compensated frame differences are higher than some (user selected) thresholds.

## Blotch detection method



Original



Blotch mask

## Reaction–diffusion method

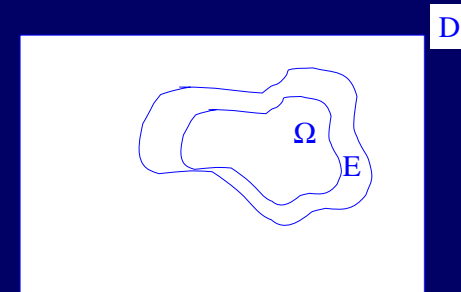
$$\frac{\partial I(\mathbf{x})}{\partial t} = \rho_D(\mathbf{x})D(\mathbf{x}) + \rho_R(\mathbf{x})R(\mathbf{x})$$

- The reaction–diffusion method (Acton *et al.*, IEEE TIP, 2001) is able to recreate the graininess and orientation of the original texture.
- It well compares with Level lines methods producing in most cases halved MSE.

- Diffusion and reaction have conflicting objectives.

– The goal of diffusion is smoothing, while the goal of reaction is pattern formation.

## Reaction–diffusion method



## Reaction–diffusion method

- The reaction–diffusion mechanism used for texture disocclusion is for a specific image location  $\mathbf{x} = (x, y, t)$

$$I^{n+1}(\mathbf{x}) \leftarrow I^n(\mathbf{x}) + \rho_D(\mathbf{x})D(\mathbf{x}) + \rho_R(\mathbf{x})R(\mathbf{x})$$

- Seeding the region with noise identically distributed as the intensities of the surrounding region

$$I^0(\mathbf{x}) = \begin{cases} Z(\mathbf{x}) & \text{if } \mathbf{x} \in D - \Omega \\ R & \text{if } \mathbf{x} \in \Omega \end{cases}$$

- $R$  is a random variable with density  $H_E(i)/|E|$  where  $H_E(i)$  is the intensity histogram for region  $E$ .

## Reaction model

- In the reaction process, we encourage formation of patterns of a given granularity and directionality, corresponding to a localized area in the frequency domain covered by a specific Gabor filter  $\mathbf{G}$

$$R(\mathbf{x}) = \mathbf{G}_x \otimes [\varphi(\mathbf{G}_x * I)]$$

- $\mathbf{G}_x$  is the Gabor filter matched to the dominant component at position  $\mathbf{x}$ .

- Given  $\mathbf{G}_i(\mathbf{x})$  Gabor filters,  $i=1, \dots, n$ .
- At each pixel, we define the dominant component as the one  $\mathbf{G}_i(\mathbf{x})$  that dominates the response of the filter that maximizes the selection criterion

$$\Pi_i(\mathbf{x}) = \frac{|G_i(\mathbf{x})|}{\max_{\omega} |G_i(\omega)|}$$

- $\varphi$  is selected as (Zhu and Mumford, IEEE TPAMI 1997)

$$\varphi(\xi) = - \left( 1 - \frac{1}{1 + (|\xi|/k)^2} \right)$$

## Diffusion model

- Since anisotropic diffusion encourages intra-region, not inter-region, smoothing, the texture can be smoothed without eliminating edges.

- A discrete representation of anisotropic diffusion PDE is

$$D(\mathbf{x}) = \sum_{d=1}^r c_d(\mathbf{x}) \nabla I_d(\mathbf{x})$$

- $c_d(\mathbf{x})$  is chosen to be (Perona and Malik, IEEE TPAMI, 1990)

$$c_d(\mathbf{x}) = \exp\left\{-\left[\frac{\nabla I(\mathbf{x})}{k}\right]^2\right\}$$

$k$  being the maximum contrast (intensity difference) within the texture pattern in the surrounding area  $\mathbf{E}$ .

- $\nabla I_d(\mathbf{x})$  is the directional derivative (simple difference) in direction  $d$  at location  $\mathbf{x}$ .

## Parameter setting

- The width of  $E$  is fixed as twice the maximum blotch width, ensuring that the width of the boundary region exceeds one full pattern period.
- The number of iterations was in the range 10-50.

## Influence of artifacts on motion estimation

- Estimated motion vectors are less reliable when an image is blotted

- The reference data extracted from the motion-compensated reference frames and used for interpolating the missing data may be erroneous

- A **block matcher** will find the general direction in which data corrupted by blotches move

- **Multiresolution** allows reduction of blotch size, with consequent little influence on the block-matching results at the lower resolution levels

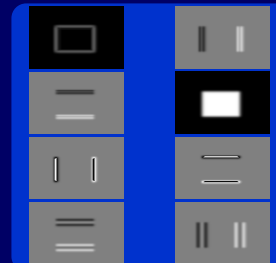
- At the higher resolutions, the blotches cover larger parts of the blocks used for matching, with consequent great influence on the matching results

## Approach

- Region-based matching approach, where the best match amounts to maximising a similarity measure between features extracted from two frames
- Each feature is a feature vector extracted using locally tuned filters

- Repeated usage of two given images via the feedback iterative procedure improves the accuracy of optical flow considerably

(Laccetti, Marcellino, Petrosino, Parallel Computing, 2003)



## Multiresolution Correlation Feedback Optical flow computation

- A correlation window is formed and centered at each pixel. 5x5 samples of error distribution around  $(u^n, v^n)$  can be computed by using the SSD. That is

$$E(u, v) = \sum_{m=-l}^l \sum_{n=-l}^l (I_t(x+m, y+n) - \Delta_b(x-u+m, y-v+n))^2$$

- 5x5 samples of response distribution can be computed as follows:

$$R_c(u, v) = e^{-kE(u, v)}$$

where  $k$  is chosen so as to make the maximum  $R_c$  among 25 samples of response distribution be a number close to unity.

## Propagation

- The optical flow vector derived at this correlation stage is then calculated as follows, according to the weighted-least-squares estimation

$$u_c^n(x, y) = \frac{\sum_u \sum_v R_c(u, v) u}{\sum_u \sum_v R_c(u, v)}$$

$$v_c^n(x, y) = \frac{\sum_u \sum_v R_c(u, v) v}{\sum_u \sum_v R_c(u, v)}$$

- Except in the vicinity of motion boundaries, the motion vectors associated with neighbouring pixels are expected to be similar.

$$u^{n+1}(x, y) = \sum_{i=-w}^w \sum_{j=-w}^w w_1(i, j) u_c^n(x+i, y+j)$$

- This constraint can be used to "regularize" the motion field

$$v^{n+1}(x, y) = \sum_{i=-w}^w \sum_{j=-w}^w w_1(i, j) v_c^n(x+i, y+j)$$

## Experiment I: Accuracy

- Let image velocity  $\mathbf{u}=(u, v)$  be represented as 3D directional vectors

$$\mathbf{V} = \frac{1}{\sqrt{u^2 + v^2 + 1}} (u, v, 1)$$

- The **angular error** between the correct image velocity  $\mathbf{V}_c$  and the estimate  $\mathbf{V}_e$

$$\psi_E = \arccos(\mathbf{V}_c \cdot \mathbf{V}_e)$$

- Three kinds of image sequences used are utilized here whose ground-truths are known.
  - They are *Translating tree 2-D*, *Diverging tree 2-D*, and *Yosemite*
- The first two simulate translational camera motion with respect to a textured planar surface. The Yosemite sequence is a more complex test case; the motion in the upper right is mainly divergent.

## Experiment I: Accuracy

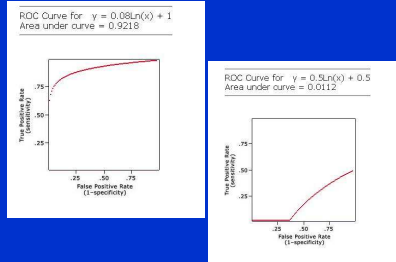
Techniques/Treet	Average error	Standard deviation	Density
Horn & Schunck	2.02°	2.27°	100%
Uras et al.	1.62°	1.52°	100%
Lucas & Kanade	2.65°	3.02°	100%
Fleet	2.56°	3.27°	100%
Nagel	2.44°	3.06°	100%
Anandan (l=3, w=3)	4.54°	3.10°	100%
Singh (step 2, l=2, w=2)	1.25°	3.29°	100%
<b>Our (l=4, w=3)</b>	<b>1.45°</b>	<b>0.88°</b>	<b>100%</b>

Techniques/Treed	Average error	Standard deviation	Density
Horn & Schunck	2.55°	3.67°	100%
Uras et al.	2.82°	2.73°	100%
Lucas & Kanade	2.76°	3.92°	100%
Fleet	6.54°	4.34°	100%
Nagel	2.94°	3.23°	100%
Anandan (l=3, w=3)	7.64°	4.96°	100%
Singh (step 2, l=2, w=2)	8.60°	5.60°	100%
<b>Our (l=4, w=3)</b>	<b>2.45°</b>	<b>2.56°</b>	<b>100%</b>

Techniques/Yosemite	Average error	Standard deviation	Density
Horn & Schunck	11.26°	16.41°	100%
Uras et al.	10.44°	15.00°	100%
Lucas & Kanade	12.04°	14.45°	100%
Fleet	13.25°	14.03°	100%
Nagel	11.71°	10.59°	100%
Anandan (l=3, w=3)	15.84°	13.46°	100%
Singh (step 2, l=2, w=2)	13.16°	12.07°	100%
<b>Our (l=4, w=3)</b>	<b>11.05°</b>	<b>10.50°</b>	<b>100%</b>

## Experiment II: *Robustness*

- We compare the SDI detection ability, with different motion estimation techniques, plotting their Receiver Operator Characteristics (ROCs)
- ROC plots the false alarm rate versus the correct detection rate of a detector
- The curves were obtained by letting  $T_1$  vary from 25 to 250, and fixing  $T_2$  to 0.001.
- The ratio of correct detections to false alarms is large
- Four test sequences were used degraded by adding artificial blotches, with fixed image intensity value (missing data)
- The sequences are *Western*, originated by film, *MobCal*, *Manege* and *Tunnel*, recorded by modern cameras.



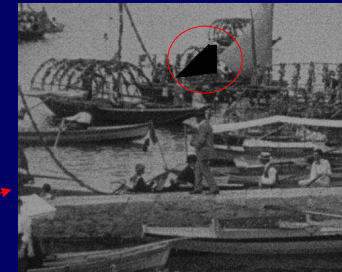
## Example



$t-1$

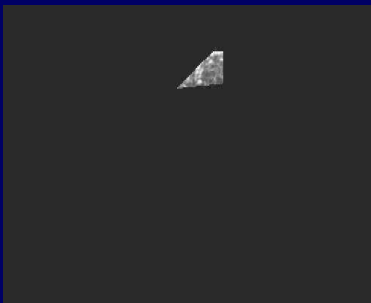
$t+1$

Reference frame



$t$

## Example



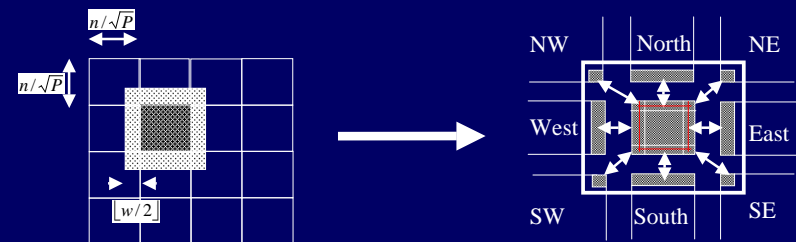
Blotch detection and seeding the region with noise



Restored frame

## Parallel algorithm

- Blotch Removal**
  - All operations are window-based operations
  - Data parallelism can be naturally exploited



## Parallel algorithm

### • Blotch Detection

- SDI computation: all the operations are pixel-based
- Motion Estimation:
  - Backward and forward motion compensation are computed at each node in an asynchronous and multithreading manner

### • Two kinds of motion vectors can be considered:

- Local motion vectors involving pixels located in a single node
- Non-local motion vectors involving pixels belonging to more than one node

- Each node is let to run asynchronously and task scheduling based on message arrival is performed

## Multi-threading

- The processing at each node is divided into two categories:

- Processing of local motion vectors can be performed independently from other nodes
- Processing of a part of a non-local motion vector can only be performed after performing all local motion vectors

### • Multi-threading at user level

- Whenever data useful for non-local motion vectors thread are exhausted, instead of idling, the node switches to the local motion vector thread.
- Once new data arrives, the node switches to the global motion vectors thread

## Multi-threading

### • Two priority ready queues are adopted:

- Tasks leading to the computation of non-local motion vectors
- Tasks leading to the computation of local motion vectors

- The algorithm was implemented on a **Beowulf** (employing 30 Pentium nodes) and on the **SP2** (employing 14 RISC6000 nodes)

- The code was written using C and the MPI library (without parallel I/O)

- I/O time for loading and collecting the image data is not considered in the reported times

## Test sequences

### • Several motion picture sequences from:

- the website Internet Moving Images Archive: Movie Collection (<http://www.archive.org/movies/>)
- Kokaram book
- kindly provided by Dyte s.r.l. (multimedia data processing firm), Italy



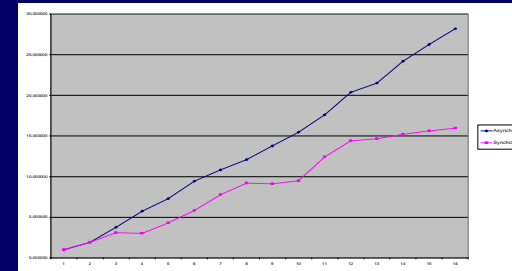


## Test sequences

- Almost-static sequence with severe blotchy noise: (view of Golden Gate Bridge)
- Complicated scene with lots of motion and heavy noise (scene of people walking around on Golden Gate Bridge)
- Scene containing some apparent motion and also obvious noise (closing up show of man and a flying flag)
- Scene with lots of motion but less noticeable noise (children playing with swings and running)

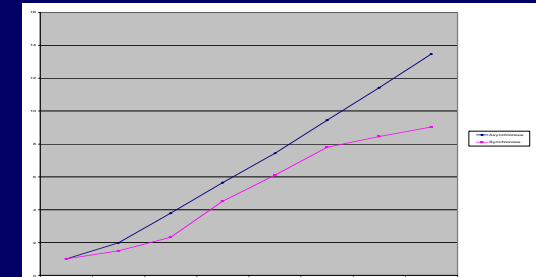


## Experiment I: *Speedup Asy. vs Sy.*

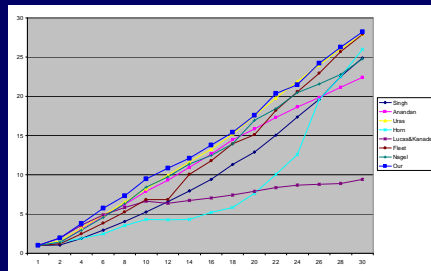


Beowulf

SP2

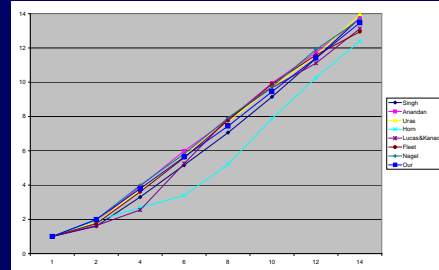


## Experiment II: *Speedup*

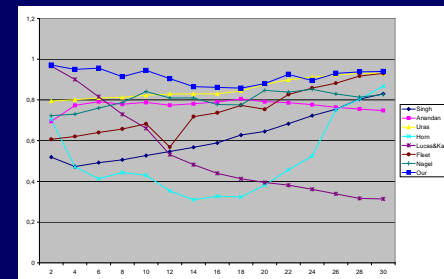


SP2

Beowulf

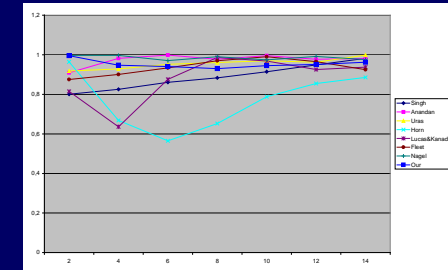


## Experiment III: *Efficiency*



Beowulf

SP2



## Experimental results

- Given a 256x256 blotched image, blotches can be restored in **2,910140** seconds on a 14-node SP2 and in **1,548352** on a 30-node Beowulf. A serial implementation takes **40,228437** seconds and **45,278277** on a single node of SP2 and Beowulf, respectively.
- For a given 256x256 blotched image, we obtained speed-ups of **13,82354** and **29,24288** using our algorithm on a **14**-node SP2 and a **30**-node Beowulf, respectively.

## Some results

.....

## On going ...

- Stopping procedure based on differences between motion vectors computed between two consecutive levels.
- Detection whether motion exists so as to exclude unnecessary motion estimation.
- Motion may only exist in part of the frame, so the detection could be carried out in a section-wise manner and spatially adaptive to different regions of each frame.

Thanks for the attention ...