### Video Reconstruction Problems Final Presentation

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youtube, june 2012: "Dangerous Rites: Vine Bungee Jumping"

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- 1 Problem Setting
- 2 Reconstruction with the ADM-Method
  - Theoretical Background
  - Implementation
  - Error Localization
- 3 Joint sparse and low rank matrix approximation
- 4 Computational Results



# The Inpainting Problem

**video inpainting:** restore lost or corrupted pixels of a video.

 $\rightarrow$  needed for digitizing videos and removing errors.

### possible errors:

- defects in old videos
- logos
- texts
- Iow resolution

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# The Model

Minimization Problem<sup>1</sup>

$$\min_{u} \frac{\mu}{2} \| \mathsf{P} u - f \|_{2}^{2} + \varphi_{\mathsf{reg}}(u)$$
 (P1)

### with

- *u* : reconstructed video
- *f* : undamaged pixels in the corrupted video
- P : projection onto undamaged pixels of the video
- $\varphi_{\rm reg}$  : regularization function

<sup>1</sup>Chan, Khoshabeh, Gibson, 2011



# **TV-Regularization**



**TV-Regularization**  $\varphi_{\rm reg} = \sum_i \|D_i u\|_2$ with  $||D_{i}u||_{2} = (\beta_{x}^{2}[D_{x}u]_{i}^{2} + \beta_{y}^{2}[D_{y}u]_{i}^{2})$  $+\beta_t^2 [\mathsf{D}_t u]_i^2)^{\frac{1}{2}}$ 

### ADM I

1. transform (P1) to constrained problem:

$$\min_{u} \quad \frac{\mu}{2} \| \mathsf{P} u - f \|_{2}^{2} + \sum_{i} \| w_{i} \|_{2}$$
  
s.t.  $w_{i} = D_{i}u \quad \forall i$ 

2. form augmented Lagrangian

$$L_{\alpha}(w, u, \lambda) = \frac{\mu}{2} \| \mathsf{P} u - f \|_{2}^{2} + \sum_{i} \|w_{i}\|_{2} + \lambda_{i}^{T}(w_{i} - D_{i}u) + \frac{\alpha}{2} \|w_{i} - D_{i}u\|_{2}^{2}$$

# ADM II

3. apply algorithm

Alternating Direction Method

FOR 
$$k = 1, 2, ...$$
 DO  
1.  $w^{k+1} = \arg \min_{w} L_{\alpha}(w, u^{k}, \lambda^{k})$   
2.  $u^{k+1} = \arg \min_{u} L_{\alpha}(w^{k+1}, u, \lambda^{k})$   
3.  $\lambda^{k+1} = \lambda^{k} - \gamma \alpha (w^{k+1} - Du^{k+1})$   
END DO

According to the theory of Glowinski and Le Tallec (1989) this algorithm converges to the solution of (P1) if  $0 < \gamma < \frac{1+\sqrt{5}}{2}\alpha$ .

### A closer look on the u-subproblem

u-subproblem:  $u^{k+1} = \arg \min_{u} L_{\alpha}(w^{k+1}, u, \lambda^{k})$ 

$$Au = b^k$$

with: •  $A = \alpha D^T D + \mu P^T P$ •  $b^k = \mu P^T f + D^T (\alpha w^{k+1} - \lambda^k)$ 



# Result (video "jet"<sup>2</sup>)



Iterations	$\mu$	$\beta_{x}$	$\beta_y$	$\beta_t$
2	10,000	1	1	0

<sup>2</sup>youtube, june 2012: "'Favorite' Jet Aircraft Takeoffs."

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### Problemsize for video "jet"

- resolution:  $512 \times 288$
- duration: 6 sec
- frame rate: 25 fps

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### $\Rightarrow$ 22,118,400 variables

### Problemsize for video "jet"

- resolution: 512 x 288
- duration: 6 sec
- frame rate: 25 fps

### Properties of A in video "jet"

- Size: 22,118,400 × 22,118,400
- Memory (sparse): 1.9 Gb
- Memory (full): 3913 Tb

### Inexact solution of the u-subproblem

Problem: Matlab backslash operator produces "memory error".

Preconditioned conjugate gradient method

•  $A = \alpha D^T D + \mu P^T P$  is symmetric and positive definite

- Incomplete Cholesky factorization as preconditioner
- Previous iteration as initial value
- PCG converges for video "jet" after 28, then 2 iterations with residuals  $r < 10^{-10}$ .



# **Overlapping Method**







### Difficulties

- Problem size and limited RAM capacity Solutions:
  - Inexact solver (PCG) for the u-subproblem
  - Overlapping method

Corrupted pixels must be known in advance.



# Corrupted Video & Dynamic Mask

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<sup>3</sup>Weickert, 1999. Picture: Wolfram Demonstrations Project, 2012.

dvnamic bitmask

# Dynamic Mask

#### corrupted video



### Corrupted Video & Reconstruction



$\sigma$	$\rho$	calculation time for mask (1280×720)	scaling factor
0.1	1	approx. 12 <sup>s</sup> /frame @ 1.6Ghz	0.3

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ПП

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# Same movie scene appears several times in neighbored frames.



ТШ

 $\Rightarrow$  use redundant information for detecting and correcting corrupted pixels

# Patch matching



- 1. divide each frame into patches *i*
- 2. find similar patches  $i_k$  in neighbored frames
- 3. store column-wise similar patches  $i_k$  in a matrix  $P_i$

# Assumption

### $P_i = L_i + S_i$

- $L_i$ : undamaged patches  $\rightarrow$  low rank matrix
- $S_i$  : corruption  $\rightarrow$  sparse matrix

# The Model

### Minimization Problem<sup>4</sup>

$$\min_{L_{i},S_{i}} \|L_{i}\|_{\star} + \lambda \|S_{i}\|_{1} \quad \text{s.t.} \ P_{i} = L_{i} + S_{i} \qquad (P2)$$

with  $\|\cdot\|_{\star}$  : nuclear norm: sum over all singular values

- $\left\|\cdot\right\|_1$  : sum of  $\ell^1\text{-norms}$  over all columns
  - $\lambda$  : regularization parameter

### Solving methods: APG or ADM

<sup>4</sup>Ji, Huang, Shen, Xu, 2011

# $\mathsf{Result}^5$



patch size	$\lambda$
16	1/16

<sup>5</sup>archive.org, june 2012: "Biplane Stunt Flying"

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### Runtime



### Memory Use



### Conclusion

	ADM+TV	ΡΜ
short runtime	$\checkmark$	×
low memory	$\checkmark$	×
high damage	$\checkmark$	×
preprocessing	$\checkmark$	×

### Outlook

### Speed up Patch Matching:

- Parallel computation of patches
- Run singular value decomposition on a GPU
- Combine ADM+TV and Patch Matching
- Different color models

# Thank you for your attention!

Any questions?