Temporally consistent gradient based video editing

Gabriele Facciolo

Technicolor - Rennes - Oct 2013

Collaborators

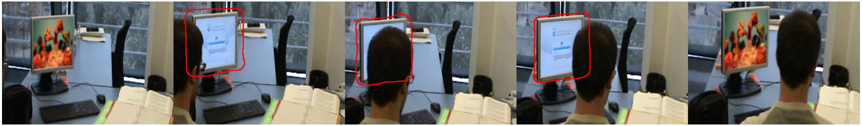
- G.F, R. Sadek, A. Bugeau, and V. Caselles. "Temporally Consistent Gradient Domain Video Editing". *EMMCVPR 2011, Saint-Petersburg.*
- R. Sadek, G.F, P. Arias, and V. Caselles. "A Variational Model for Gradient-Based Video Editing". *IJCV 2013.*

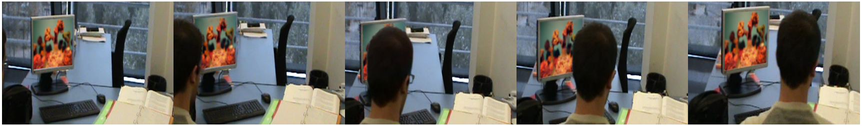
Motivation

sources/destinations cloning seamless cloning

[Pèrez et al. ’03]

Motivation





Outline

Model

Discretization

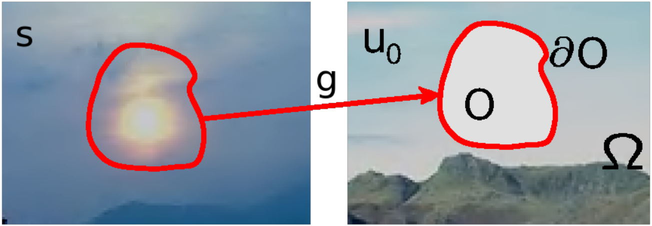
Results

Perspectives and Conclusion

Poisson edit

$$\min_u \int_{O \subset \Omega} \|\nabla u - \mathbf{g}\|^2 \mathrm{d}x \qquad \text{with} \qquad \underbrace{u|_{\partial O} = u_0}_{\text{Dirichlet boundary cond.}}$$

- $O \subset \Omega \subset \mathbb{R}^2$: edit domain
- $u : O \to R$: solution image
- $u_0 : \Omega \to \mathbb{R}$: target image
- $\mathbf{g} : O \to \mathbb{R}^2$: guidance field (i.e. ∇s)



[Pérez et at. 03]

Poisson edit

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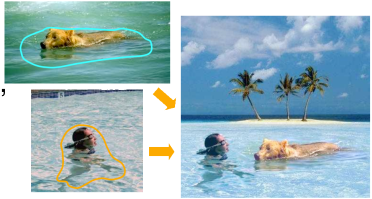
[Pérez et at. 03]

From Image to Video Edit

Gradient domain image edit [Pèrez et. al., Georgiev, Hagenburg et. al.]...

- manipulate image gradients
- applications: seamless compositing, tone mapping, shadow removal, matting, inpainting...



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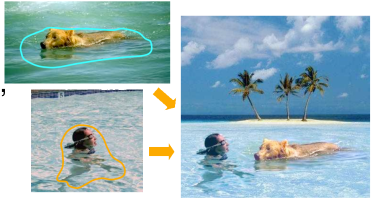
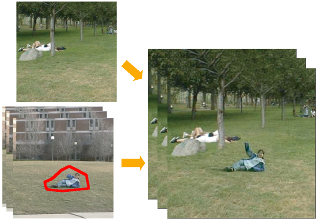


Extension to video [Wang et. al., Bhat et. al.]...

- applications: object insertion /removal, nonphotorealistic rendering, flickering removal...
- key: temporal consistency



Unwrap Mosaics: A new representation for video editing*

Alex Rav-Acha
Weizmann Institute of Science

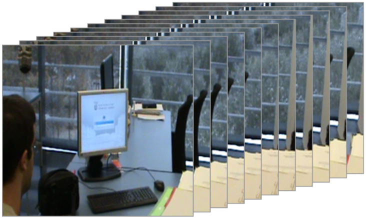
Pushmeet Kohli
Microsoft Research

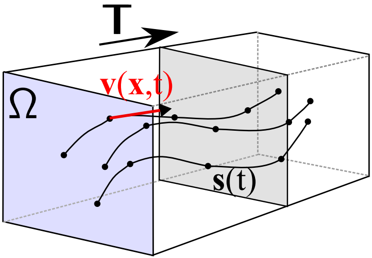
Carsten Rother
Microsoft Research

Andrew Fitzgibbon
Microsoft Research

Modeling Temporal Consistency

- Video as a volume / stack of frames $u : (\Omega \times \mathbb{T}) \to \mathbb{R}$
- Points **should "look uniform"** along their trajectories $\mathbf{s}(t)$





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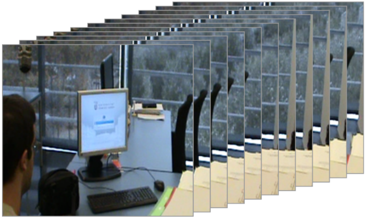
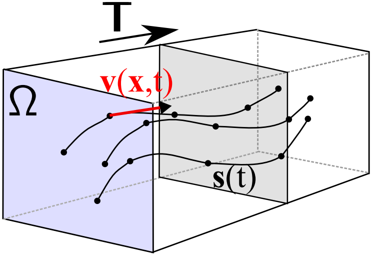




- The motion field $\mathbf{v}(\mathbf{x}, t) : (\Omega \times \mathbb{T}) \to \mathbb{R}^2$ characterizes all the trajectories

Brightness Constancy Assumption

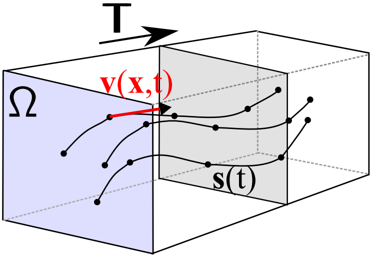
Points should have constant color along their trajectories $\mathbf{s}(t)$

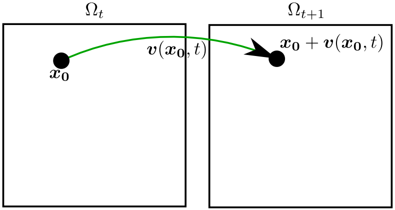
$$\frac{\mathrm{d}}{\mathrm{d}t} u(\mathbf{s}(t), t) = 0$$

Applying chain's rule

$$\partial_{\mathbf{v}} u(\mathbf{x}, t) := \mathbf{v}(\mathbf{x}, t) \cdot \nabla u(\mathbf{x}, t) + \partial_t u(\mathbf{x}, t) = 0$$

where $\partial_{\mathbf{v}} u$ is the convective derivative





Brightness Constancy Assumption

Example of brightness NON constancy

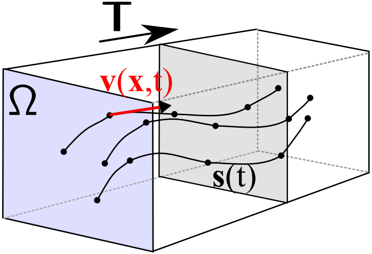
Global Brightness Change Assumption

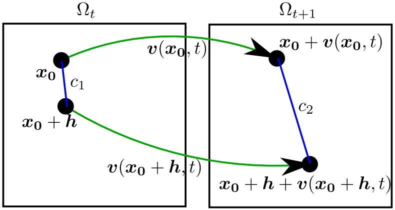
Points “look uniform” along their trajectories even in presence of a global brightness change

$$\partial_{\mathbf{v}} u(\mathbf{x}, t) = g(t)$$

Taking the spatial gradient on both sides

$$\boldsymbol{\nabla} \partial_{\mathbf{v}} u(\mathbf{x}, t) = 0$$





Modeling Motion

Feature Tracking + Parametric Model

1. Tracking: “Lagrangian” view of the motion

Modeling Motion

Optical Flow

1. Tracking: “Lagrangian” view of the motion
2. Optical flow: “Eulerian” view of the motion

Modeling Motion

Optical Flow

1. Tracking: "Lagrangian" view of the motion
2. Optical flow: "Eulerian" view of the motion $\Leftarrow$

Optical Flow vs. True Motion

True Motion (motion field)

object motion projected on the image plane

Optical Flow

estimation of the apparent motion (velocity) of objects within an image sequence

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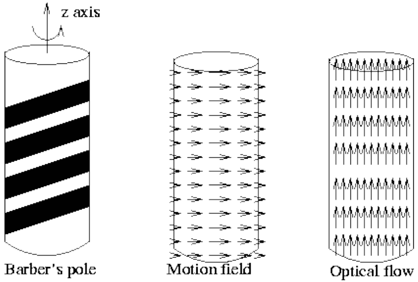

http://homepages.inf.ed.ac.uk/rbf/CVonline

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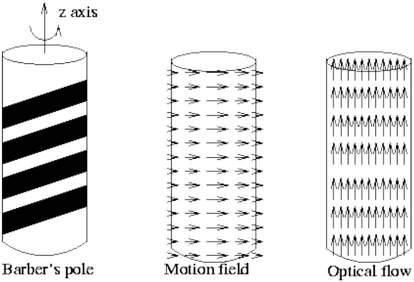


http://homepages.inf.ed.ac.uk/rbf/CVonline

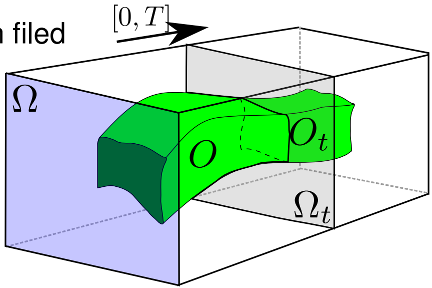
We use the optical flow as an approximation of the true motion

Gradient Based Video Edit (GBVE)

$$\min_{u} \int_0^T \int_{O_t} \|\nabla \partial_{\mathbf{v}} u(\mathbf{x}, t)\|^2 \, \mathrm{d}\mathbf{x} \, \mathrm{d}t$$

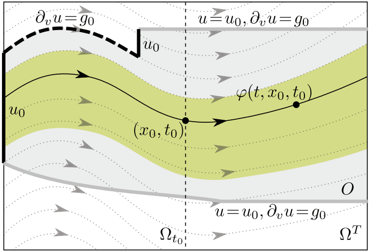
s.t. $u|_{\partial O} = u_0$

- $O \subset (\Omega \times \mathbb{T}) \subset \mathbb{R}^3$: edit domain
- $u_0 : (\Omega \times \mathbb{T}) \to \mathbb{R}$: target video
- $\mathbf{v} : (\Omega \times \mathbb{T}) \to \mathbb{R}^2$: motion filed
- $u : O \to \mathbb{R}$: solution

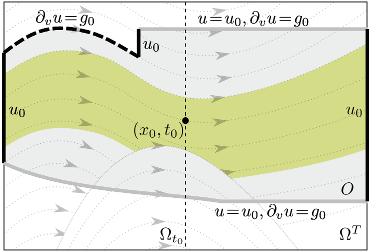


Gradient Based Video Edit (GBVE)

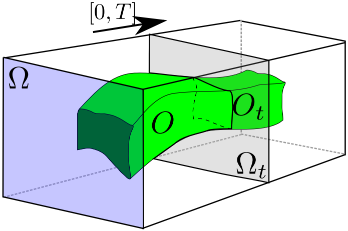
Boundary conditions



One-lid problem.



Two-lid problem.



Discretization

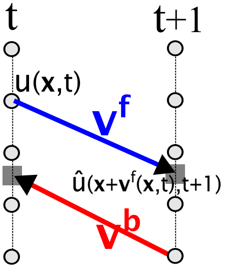
$$\min_{u} \sum_{(\boldsymbol{x},t)\in\widetilde{O}} \|\boldsymbol{\kappa}(\boldsymbol{x},t)\nabla\partial_{\boldsymbol{v}}u(\boldsymbol{x},t)\|^2 \quad + \quad BC$$

- Equivalent to a sparse linear least squares: $\min_u \|Au - b\|^2$
- Forward and backward flows $\boldsymbol{v}^f(\boldsymbol{x},t)$ and $\boldsymbol{v}^b(\boldsymbol{x},t)$, yield two convective derivative discretizations

$$\partial^f_{\boldsymbol{v}}u(\boldsymbol{x},t) := \hat{u}(\boldsymbol{x}+\boldsymbol{v}^f(\boldsymbol{x},t), t+1) - u(x,t)$$

$$\partial^b_{\boldsymbol{v}}u(\boldsymbol{x},t) := u(\boldsymbol{x},t) - \hat{u}(\boldsymbol{x}+\boldsymbol{v}^b(\boldsymbol{x},t), t-1)$$

where $\hat{u}(\boldsymbol{x},t)$ is the interpolation of u



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$$\partial^f_{\boldsymbol{v}} u(\boldsymbol{x},t) := \hat{u}(\boldsymbol{x} + \boldsymbol{v}^f(\boldsymbol{x},t), t+1) - u(x,t)$$

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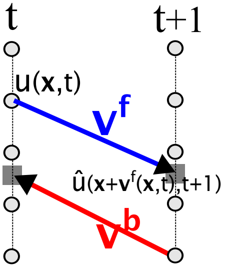
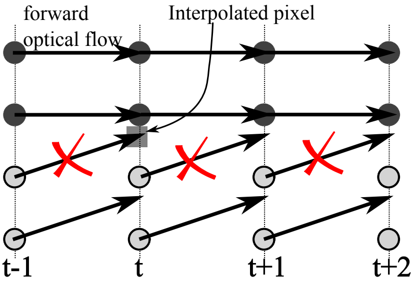


- $\kappa(\boldsymbol{x},t)$: occlusion tensor

Occlusions Handling



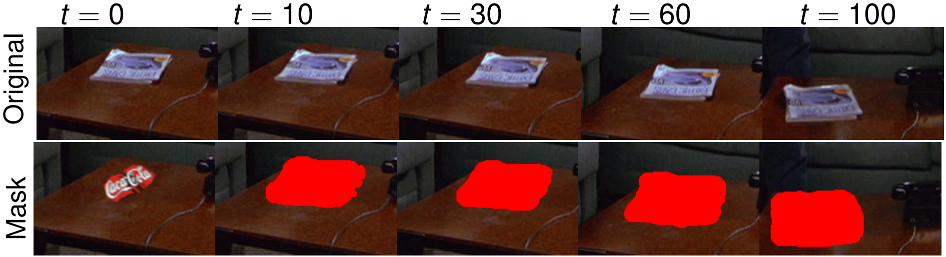
Ω_{t-1}

Ω_t

occlusions on Ω_{t-1}

$\kappa(\boldsymbol{x}, t)$ removes flow vectors corresponding to occlusions in u_0

First GBVE experiment



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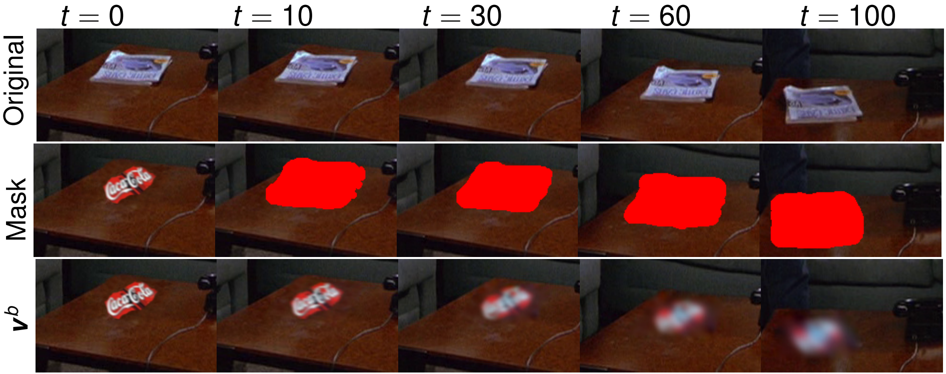

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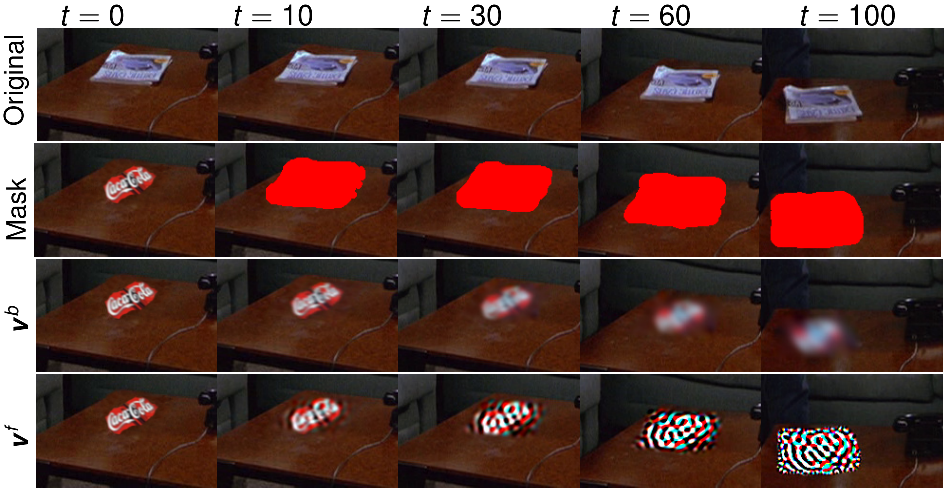
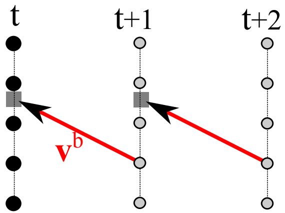


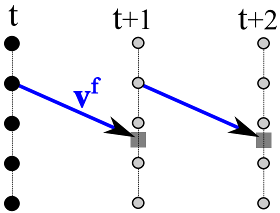
Analysis of discretized convective derivatives

- Constant translation motion, without brightness changes
- Suppose zero-energy solutions, so: $\partial_{\boldsymbol{v}}^{b/f} u(\boldsymbol{x}, t) = 0 \quad \forall(\boldsymbol{x}, t)$
- Denote interpolations M^b and M^f, so that

$$u(\cdot, t+1) = M^b\, u(\cdot, t) \qquad \Leftarrow \text{(blur)}$$

$$u(\cdot, t+1) = (M^f)^{-1}\, u(\cdot, t) \qquad \Leftarrow \text{(inverse smoothing)}$$





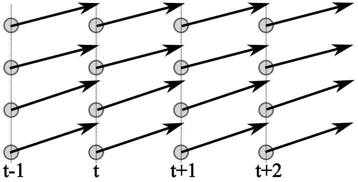
Key Obs.: $M^b$and $(M^f)^{-1}$ have somewhat opposed effects

DSCD: Deblurring Scheme for the Convective Derivative

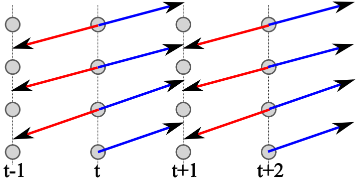
The idea is to **alternate** between

- $\mathbf{v}^f$-scheme at even frames (sharpens) and
- $\mathbf{v}^b$-scheme at odd frames (blurs)

to moderate each other's effects

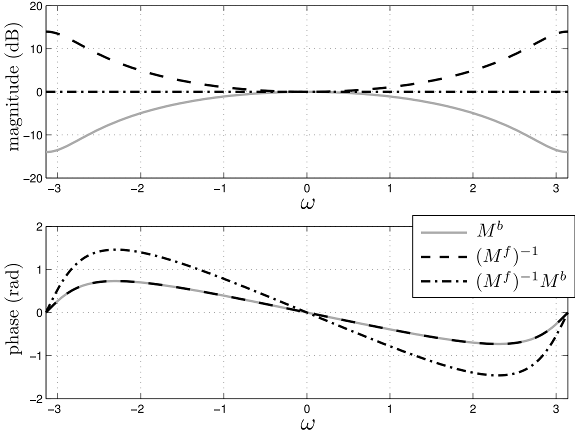


$\mathbf{v}^f$-scheme



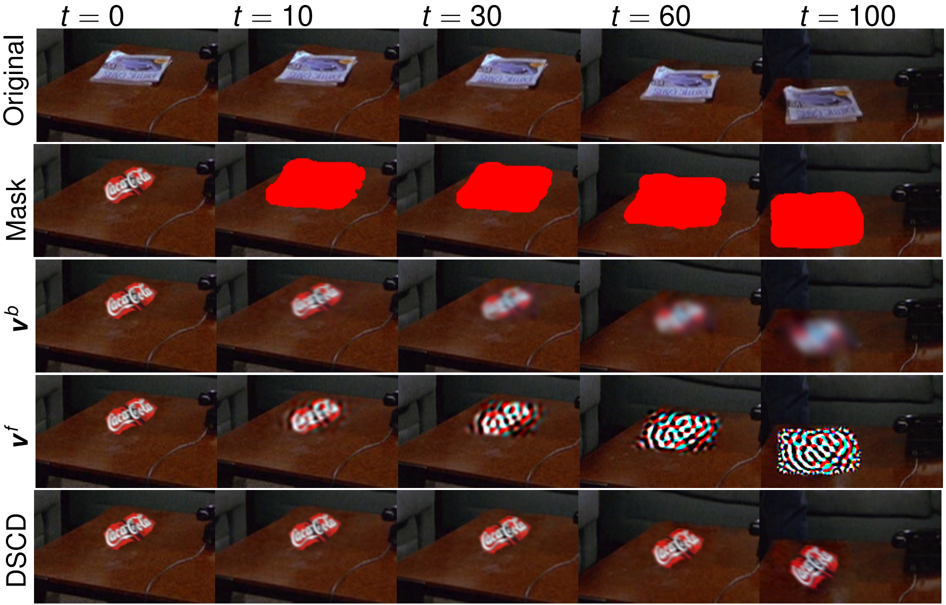
DSCD

DSCD

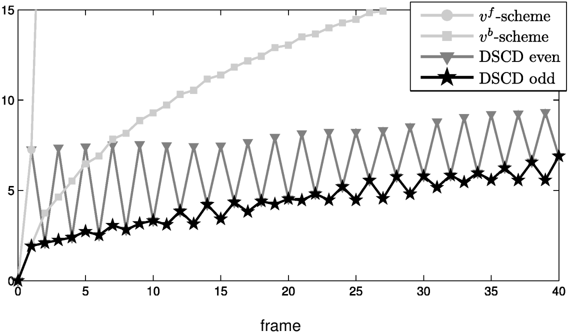


Analysis of a zero-energy solution for a one-lid problem, with a purely translational motion. Frequency responses of the M^b and $(M^f)^{-1}$ filters, and their composition $(M^f)^{-1}M^b$.

GBVE with DSCD

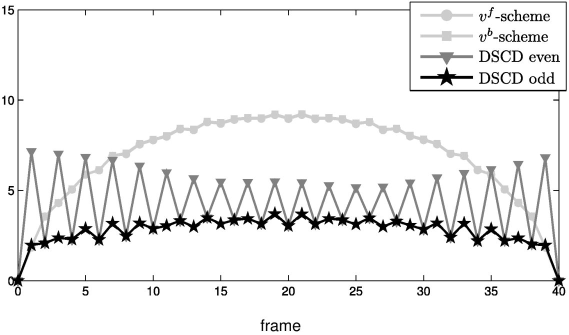


DSCD one-lid



RMSE w.r.t. the ground truth for a synthetic problem with a constant translation of $\boldsymbol{v_0} = [-0.425, 0]$ px/frame.

DSCD two-lid



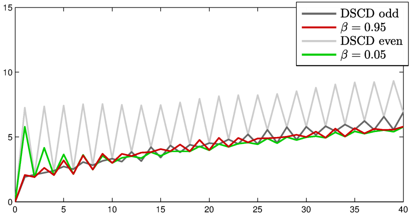
RMSE w.r.t. the ground truth for a synthetic problem with a constant translation of $\boldsymbol{v_0} = [-0.425, 0]$ px/frame.

DSCD - gory details

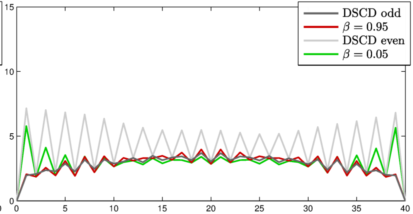
In practice, optimize a convex combination of the even and odd models

$$E_\beta = \beta E_{\boldsymbol{\kappa}}^{\text{odd}} + (1-\beta) E_{\boldsymbol{\kappa}}^{\text{even}},$$

with $\beta = 0.05$



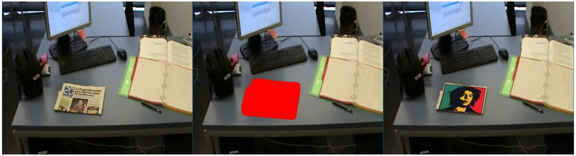
[One-lid case.]



[Two-lids case]

Results 1

Illumination chenages

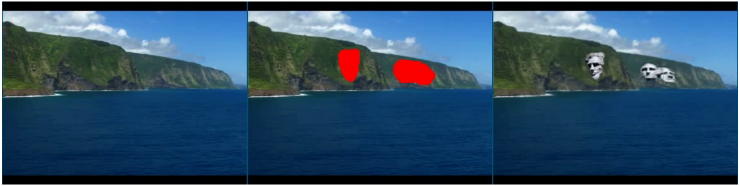


brightness constancy assumption

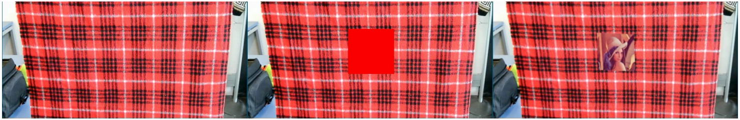
global brightness change assumption

Results 2

Deformations & Zoom



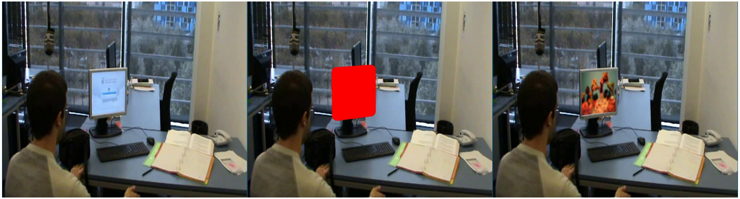
cliff



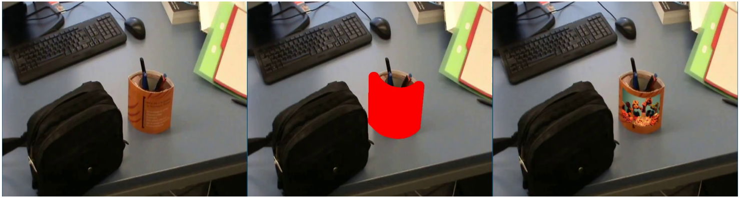
cloth

Results 3

Occlusions



screen



pen-holder

Discussion

- The GBVE algorithm relies extensively on the optical flow, unfortunately getting an artifact-free optical flow is hard.
- Sometimes tracking is easier (i.e. with markers).
  The Lagrangian modeling is more adequate when tracking can be done and motion is rigid.
- GBVE performs well specially with non-rigid objects, if the flow is available. While extracting trajectories from the field introduces drift.

Discussion

<table>
<tr><th>Eulerian modeling</th><th>Lagrangian modeling</th></tr>
<tr><td>Pros:
no need for parametric model
sometimes flow is available but tracking is not feasible</td><td>Pros:
precise for parametric motions
no long term degradation</td></tr>
<tr><td>Cons:
long term degradation
dependent on the quality of flow</td><td>Cons:
requires markers to track
drift if extracted from flow
artifacts if wrong parametric model is used</td></tr>
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Perspectives

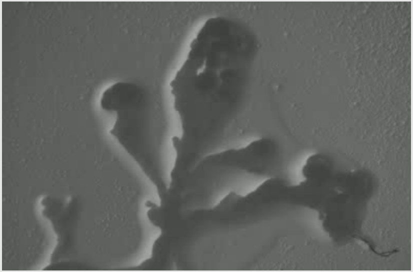
Use the Global Brightness Change Assumption

[The Cure, Charlie Chaplin, 1917]

Perspectives

Use the Global Brightness Change Assumption

to estimate motion in biological sequences



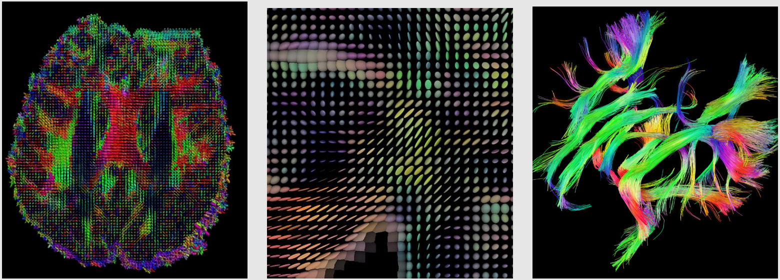
[Marc Durand (MSC Lab., Paris Diderot University),

http://perso.telecom-paristech.fr/∼delon/Demos/Flicker_stabilization/]

Perspectives

DSCD for simulation?

Diffusion tensor imaging (diffusion MRI) produces an Eulerian description of a field



[http://www.humanconnectomeproject.org/gallery/]

Conclusion

- Presented a functional for gradient domain video editing with temporal consistency
- Proposed Deblurring Scheme for Convective Derivative: to reduce artifacts introduced by the discretization of the temporal consistency term
- Discussed limitations and possible uses

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- Proposed Deblurring Scheme for Convective Derivative: to reduce artifacts introduced by the discretization of the temporal consistency term
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Thank you.

More results and MATLAB implementation available @
`http://gpi.upf.edu/static/gbve12/`