

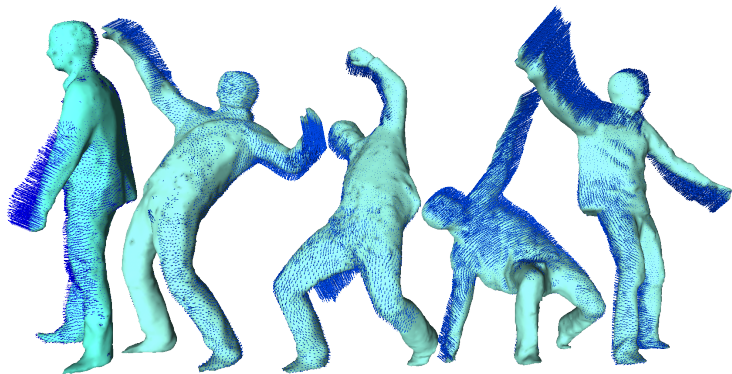
Surface Flow from Visual Cues

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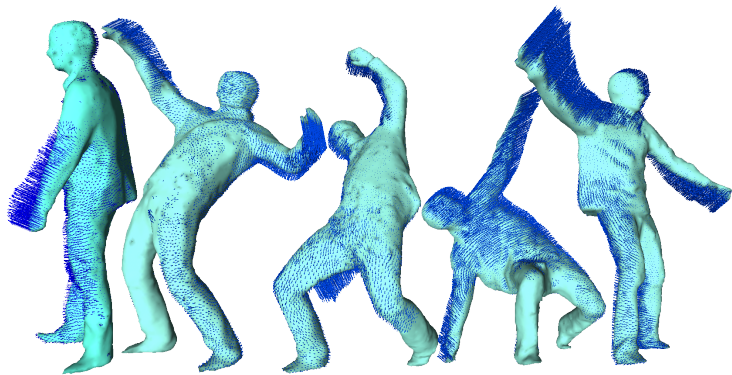


Problem: Surface Flow Estimation



Instantaneous dense motion field over a 3D surface

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Instantaneous dense motion field over a 3D surface

Motivations: Strong Low-level information for

- ▶ Tracking, segmentation
- ▶ Gesture recognition, real-time interactions

Problem Statement

Available data:

Expected Output

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- ▶ N image streams

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- ▶ 3D surface stream (independent in time)

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- ▶ N image streams
- ▶ 3D surface stream (independent in time)

Expected Output

- ▶ Instantaneous dense motion field at each point of the surface



Dense Motion Recovery: Strategies

Monocular case strategy: Optical Flow [Horn & Shunck], [Lukas-Kanade], ...

- ⇒ Image intensity variations + Smoothing constraint
- ⇒ Usually no prior on the observed scene

Dense Motion Recovery: Strategies

Multicocular case strategy: Scene flow [Vedula 2001]

[Vedula 2005]

Multiple optical flow merging

⇒ Regularization is performed in the image space

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⇒ Limited to small motions

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[Huguet 2007] and [Li 2008] and [Rabe 2010]

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Variational approach: shape + scene flow approximation

⇒ Non-linear framework

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Variational approach: shape + scene flow approximation

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Shape Matching or Tracking

Scene Flow provided as a by-product

⇒ Assumption on the scene observed

Dense Motion Recovery: Strategies

Our strategy:

Exploit surface information, mesh processing tools

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Our contribution:

A linear framework:

- ▶ that combines
 - visual constraints
 - surface deformation constraints
- ▶ that allows:
 - for coarse to fine refinement
 - to recover large motion as well as motion details

Approach

Visual cues constraints:

Regularization constraints:

Approach

Visual cues constraints:

- ▶ Dense normal flow
 - By pixel
 - Only for small motion
 - Not enough constraint



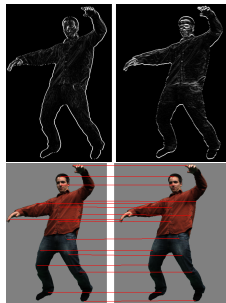
Regularization constraints:

Approach

Visual cues constraints:

- ▶ Dense normal flow
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- ▶ Sparse temporal feature matching
 - On the image or the surface
 - Handle Large motion
 - Still not enough constraint

Regularization constraints:



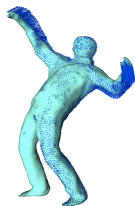
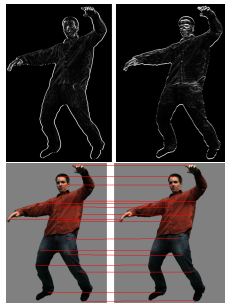
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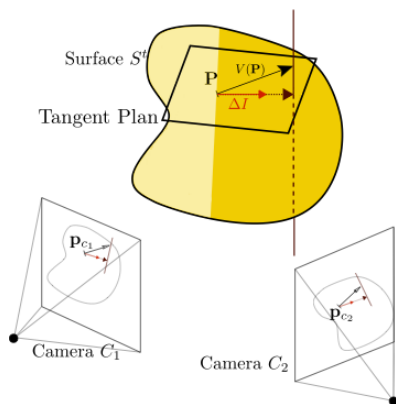
Regularization constraints:

- ▶ Smoothness of the motion field



Visual Cues : Normal Flow

Flow hypothesis:



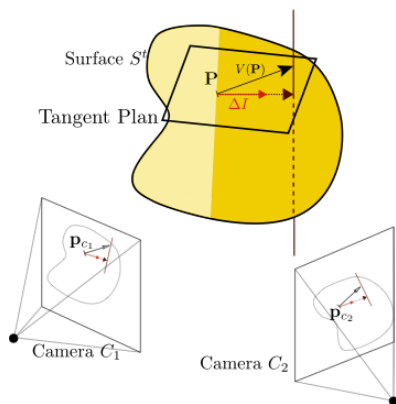
► 2D **dense** constraints:

One constraint by visible point by camera

$$\nabla I_c^t \cdot v_c^t + \frac{dI_c^t}{dt} = 0$$

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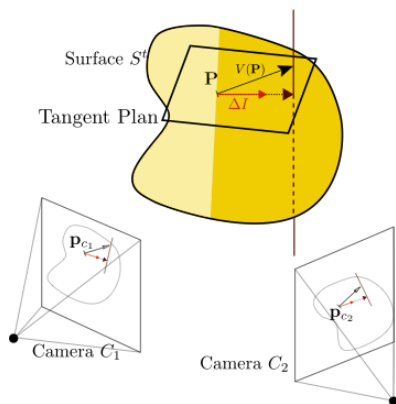
- ▶ **2D dense** constraints:
One constraint by visible point by camera
- ▶ Aperture problem even in 3D [Vedula 2005]

⇒ **Need some sort of regularization**

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Visual Cues : Normal Flow

Flow hypothesis:



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⇒ **Need some sort of regularization**

⇒ **Only small displacement estimation**

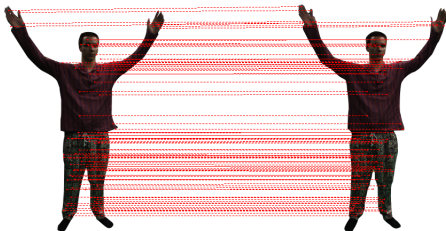
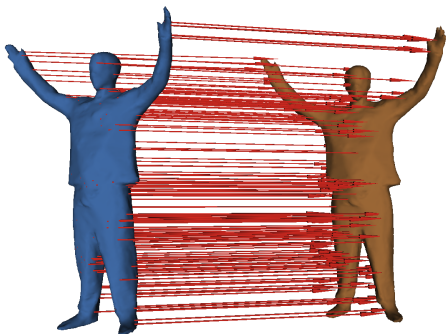
$$\nabla I_c^t \cdot v_c^t + \frac{dI_c^t}{dt} = 0$$

Visual cues: Feature points

Sparse constraints: 2D and 3D
Feature points

- ▶ Detection
- ▶ Description
- ▶ Correspondence matching in time.

⇒ **Large displacement estimation**



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- ▶ Global: Horn & Schunck
 - ⇒ Smoothness hypothesis **usually not satisfied** in 2D
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3D Strategy

- ▶ Smoothness on the surface is global
- ▶ Extension of Horn & Schunck to 3D
 - ⇒ Smoothness hypothesis **usually satisfied** in 3D

Analogy with standard mesh deformation

Both look for the best displacement field that satisfies all the constraints. But constraints are different.

Standard mesh deformation:

Constraints:

- ▶ Anchors
- ▶ User displacement inputs

Regularization:

- ▶ "As-Rigid-As-Possible"
[Sorkine 2005]

⇒ Laplacian framework

Surface flow:

Constraints:

- ▶ Dense normal flow constraints
- ▶ Sparse 2D and 3D feature points

Regularization:

- ▶ Smoothness term

⇒ Laplacian framework

Optimization

$$\arg \min_v \left[\lambda_{fe}^2 \mathbf{E}_{Features} + \lambda_{fl}^2 \mathbf{E}_{Flow} + \lambda_s^2 \mathbf{E}_{Smooth} \right]$$

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Data term differentiation yields:

$$\mathbf{A}V^t + \mathbf{b} = \mathbf{0}$$

Smoothness term differentiation yields:

$$\mathbf{L}V^t = \mathbf{0}$$

with \mathbf{L} the Laplacian matrix (mesh connectivity matrix).

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Final linear system of equation:

$$\begin{bmatrix} \mathbf{L} \\ \mathbf{A} \end{bmatrix} \mathbf{V}^t + \begin{bmatrix} \mathbf{0} \\ \mathbf{b} \end{bmatrix} = \mathbf{0}$$

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\implies Highly **sparse linear** system

Implementation

Normal flow constraints do not hold in the case of large displacement.

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⇒ Coarse to fine strategy:

- ▶ 1st pass : Large motions
- ▶ 2^{de} pass : Motion details

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⇒ Coarse to fine strategy:

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Iterative strategy : 2 successive minimizations

- 1 Constraints given by the 2D and 3D feature points
- 2 First minimization and creation of a **flowed** surface S'
- 3 Back-projection of S' onto the images
- 4 Normal flow computation
- 5 Second minimization (feature points = anchors)

Evaluations

- ▶ Quantitative : Synthetic data
- ▶ Comparison
- ▶ Qualitative : Real data

Synthetic data

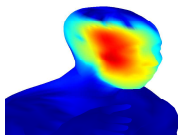
Results

on synthetic data
for quantitative evaluation

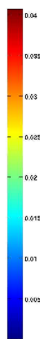
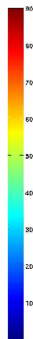
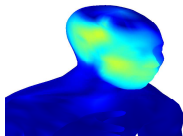
10 video streams

Synthetic data

feature points
constraints



feature points
constraints
+
Normal flow
constraints

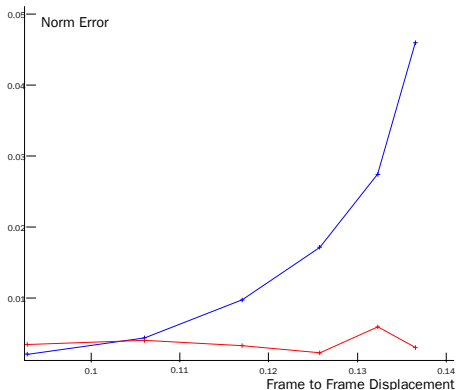
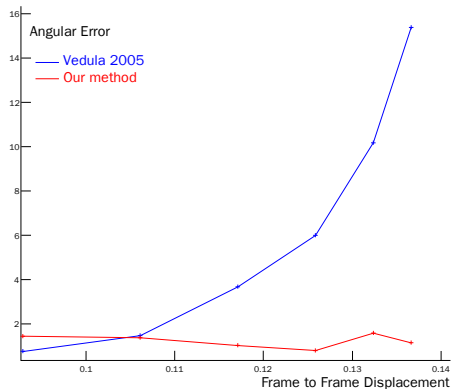


Angular

Norm

Cumulated error over the sequence

Comparison: Vedula 2005, Optical Flow integration



Error measure in orientation (degrees) and amplitude between ground truth and estimated displacements.

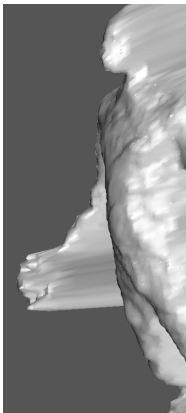
Real data

Results

on the Flashkick sequence
(University of Surrey)

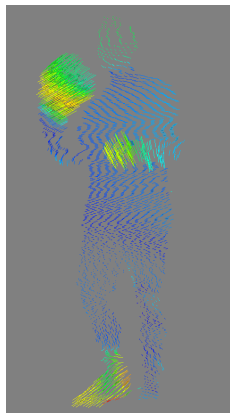
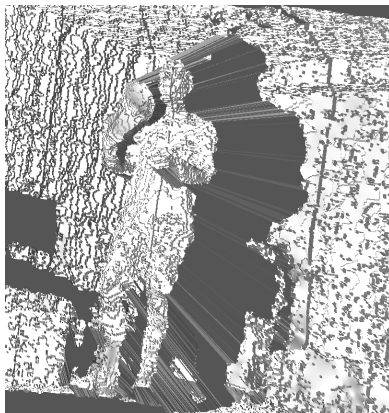
8 video streams

Extension to Point Clouds



Swiss Ranger SR4000 176×144 , two color cameras, 2Mpixels.

Extension to Point Clouds



Kinect : 640×480 , one color camera, same resolution.

Conclusion

Contribution:

- ▶ Unified framework for dense flow estimation on a surface
- ▶ Linear formulation \implies Efficient and fast
- ▶ Handle both large and small displacements

Limitation:

- ▶ Good texture information required

Perspectives:

- ▶ Real-time implementation
- ▶ Multi-scale approach for a better normal flow integration

Thank you for your attention
Questions?