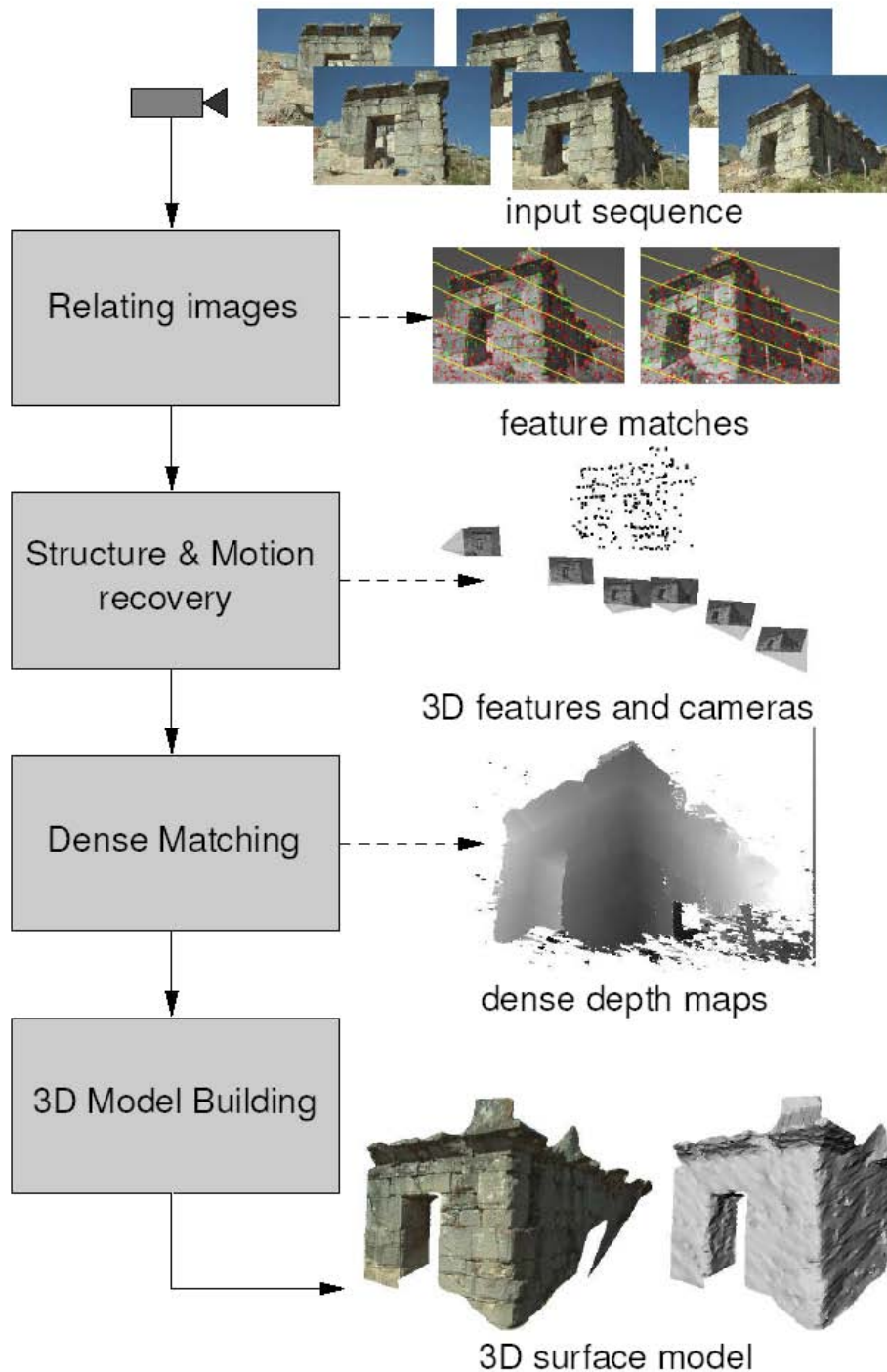


Computational 3D Photography

Extracting Shape, Motion and Appearance from Images

Marc Pollefeys
ETH Zurich

Qualcomm AR lecture
29 November 2011



(Pollefeys et al. ICCV98)

...
(Pollefeys et al. IJCV04)

Video → 3D model



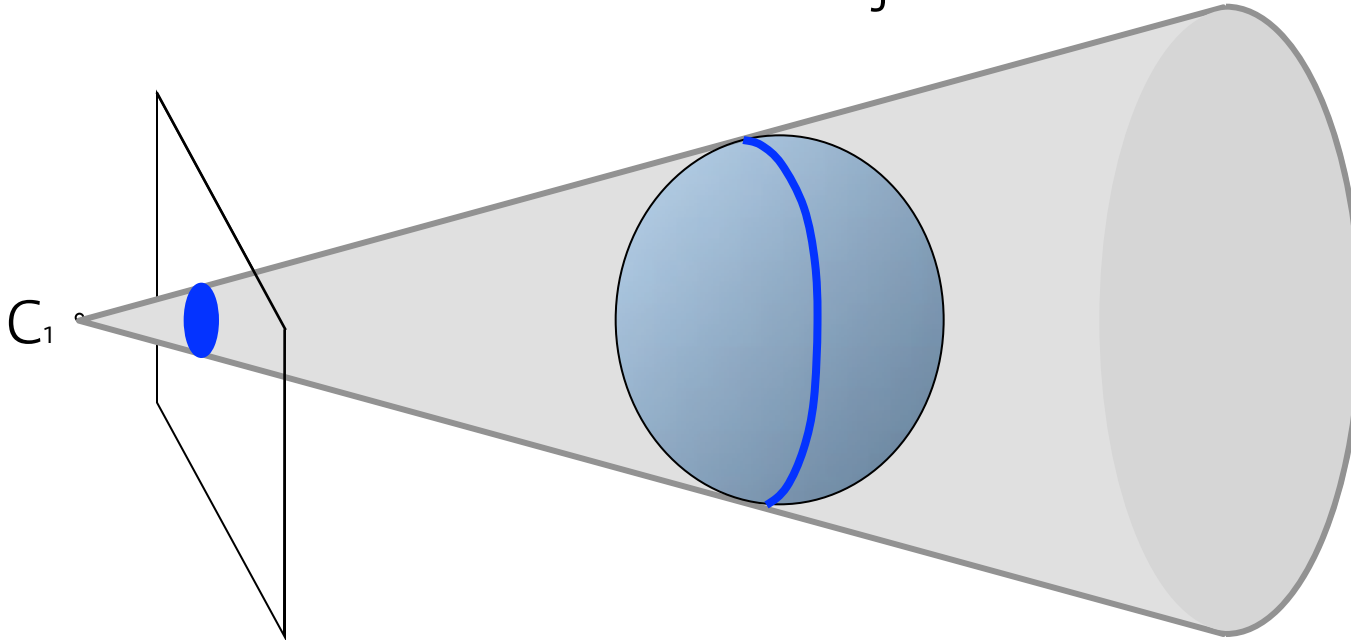
accuracy $\sim 1/500$ from DV video (i.e. 140kb jpegs 576x720)

Talk outline

- Introduction
- Object modeling
- Scene modeling
- People/event modeling
- Summary and conclusion

2D \rightarrow 3D reconstruction: silhouette constraints

Additional constraint for closed objects

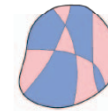


Silhouettes

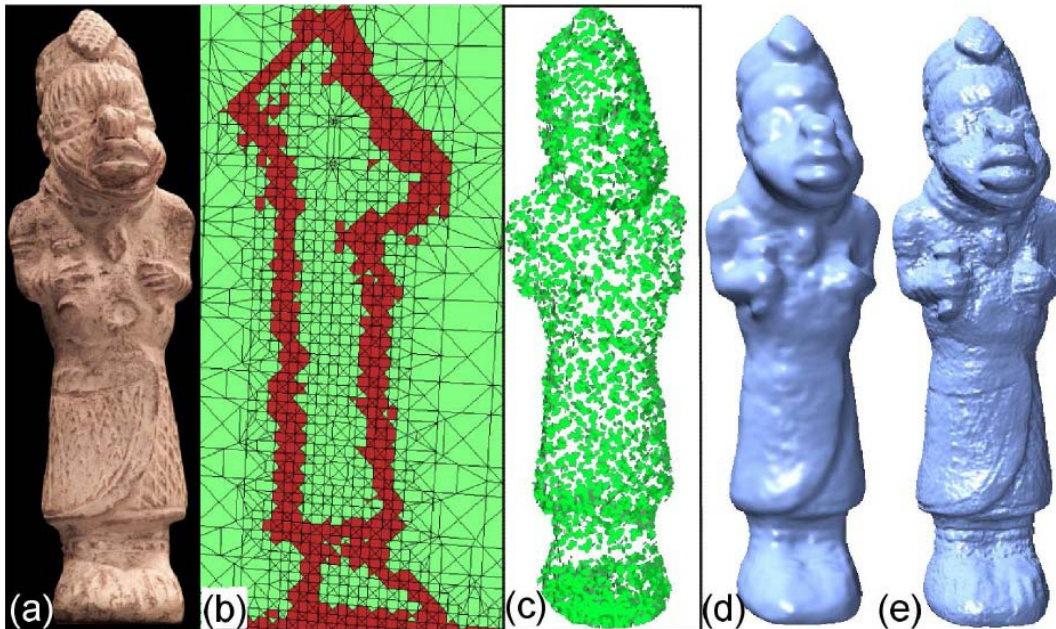
- object inside cone (visual hull)
- object tangent to cone (rim)

Multi-view 3D object reconstruction

- Combine dense matching with silhouette constraints
(Compute graph min-cut to obtain watertight surface)
 - Exact silhouettes (Sinha & Pollefeys ICCV05)
 - Photo-consistency adaptive tetrahedral mesh (Sinha et al. ICCV07)



(two-colored
rim-mesh)

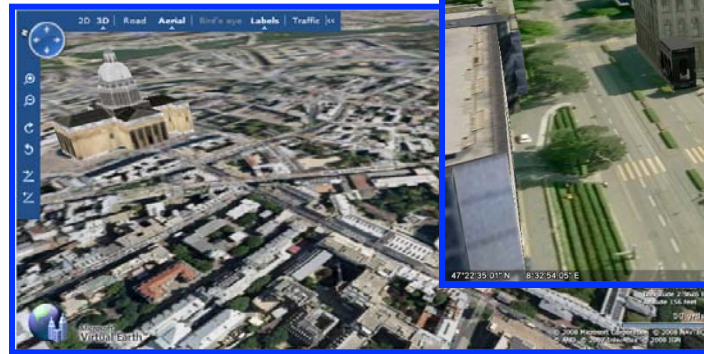


Talk outline

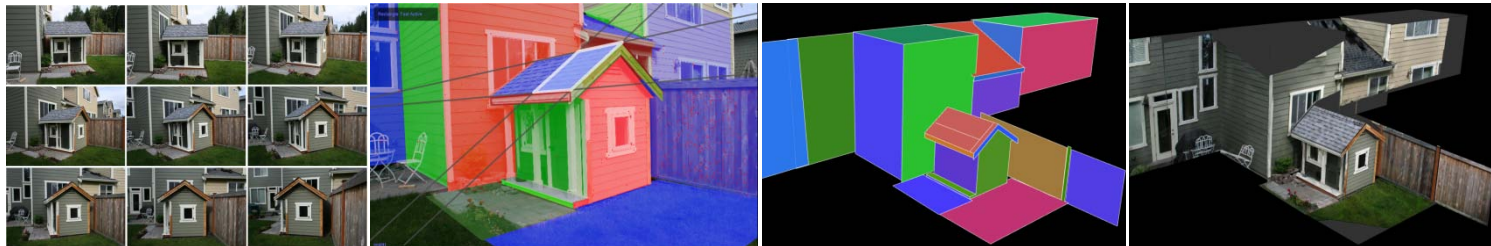
- Introduction
- Object modeling
- Scene modeling
- People/event modeling
- Summary and conclusion

Modeling the world

- Need for 3D models of real world



e.g. interactive 3D modeling of architecture (Sinha et al. Siggraph Asia 08)

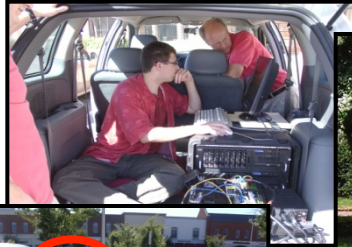


collaboration with Microsoft Research

Fast automated video-based modeling of cities



2x4 cameras
1024x768@30Hz



capture ≈ 1 TB/hour raw video data



GPS/INS system

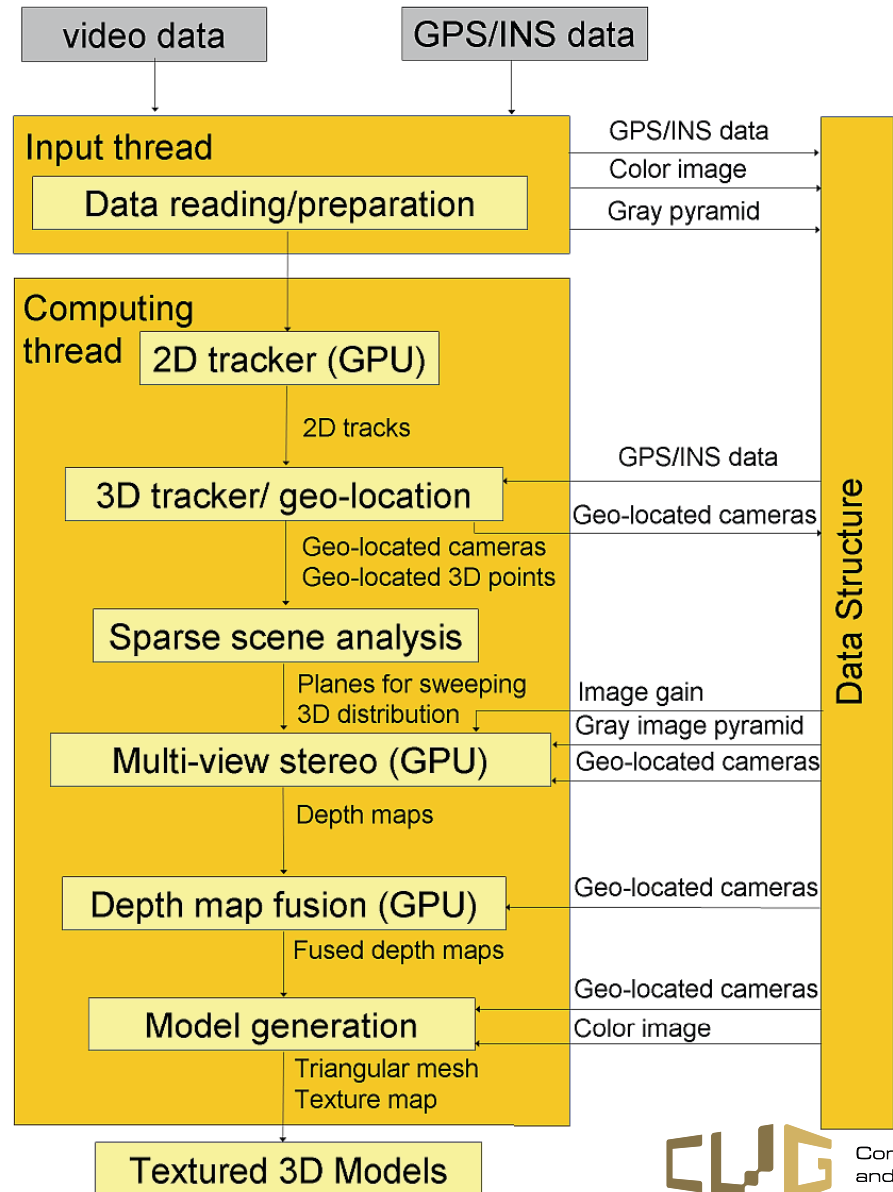
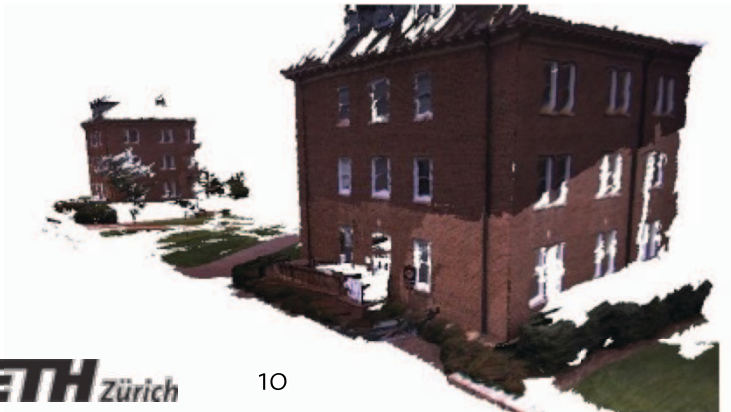


Computational 3D Photography

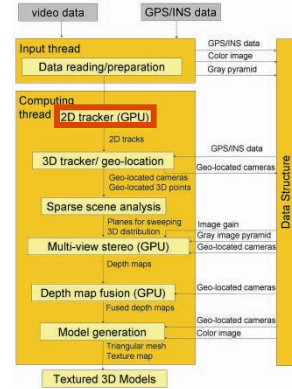
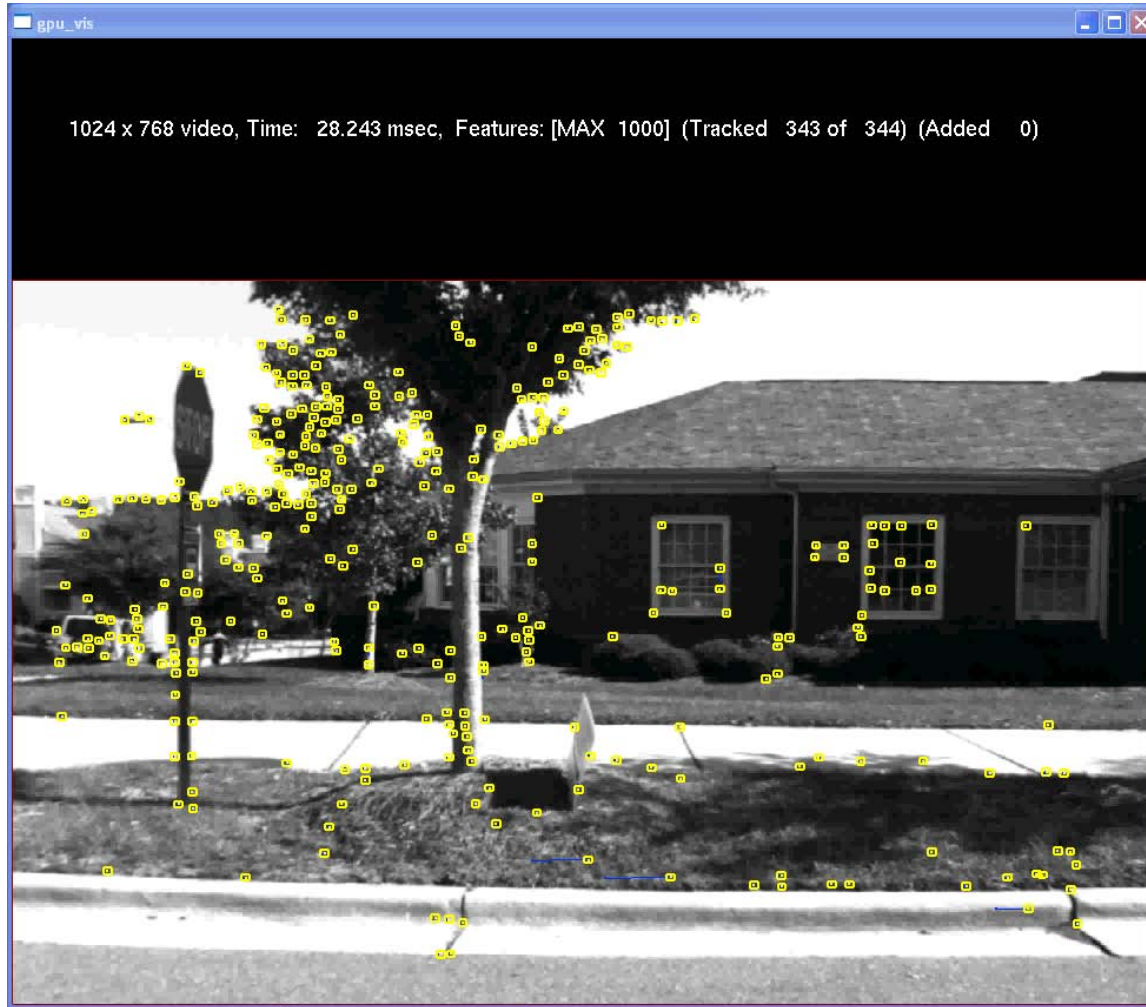
Fast video-based modeling of cities

Fast video processing pipeline

- up to 26Hz on single CPU/GPU
- Most image processing on GPU (x10-x100 faster)
- Exploits urban structure
- Generates textured 3D mesh (Pollefeys et al. IJCV, 2008)



2D Feature Tracker



fast GPU-based feature tracking
(Sinha et al. MVA07, Zach et al.08)

+ tracking of exposure changes
(Kim et al. ICCV07)



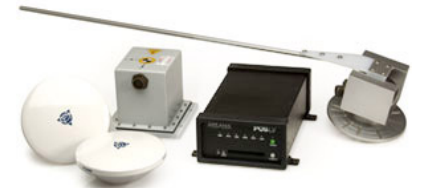
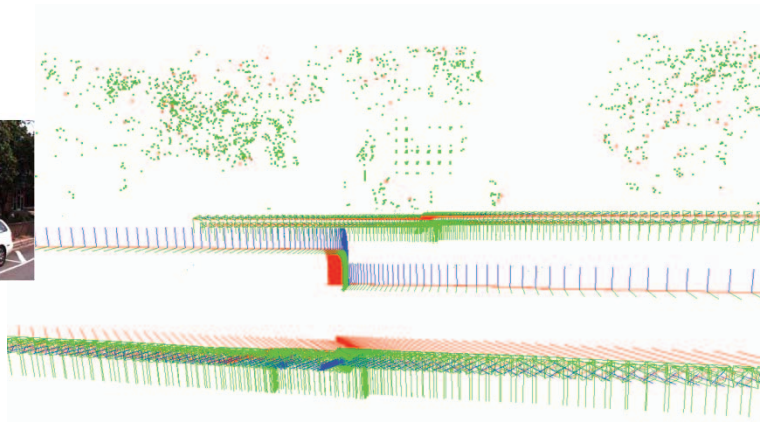
Graphics Processor Unit (GPU)
(e.g. 240 processing cores)

http://cs.unc.edu/~ssinha/Research/GPU_KLT/
<http://cs.unc.edu/~cmzach/opensource.html>

tracks 1000 features at 200Hz

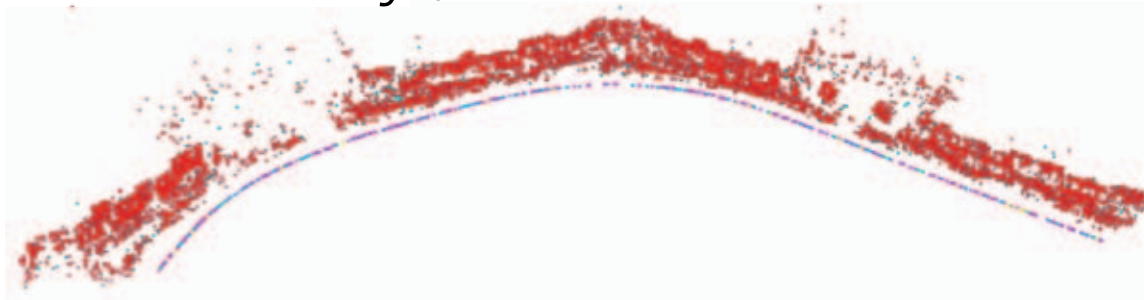
3D Tracker / Geo-location

- Fusion of 2D video tracks and INS/GPS

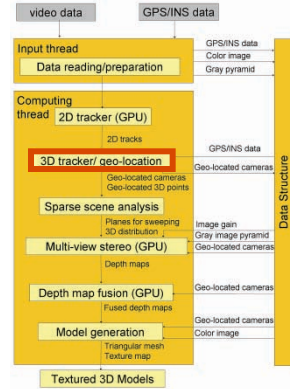


Inertial Navigation System (INS)
Global Positioning System (GPS)

or use 2D video tracks only (need to deal with drift, see later)



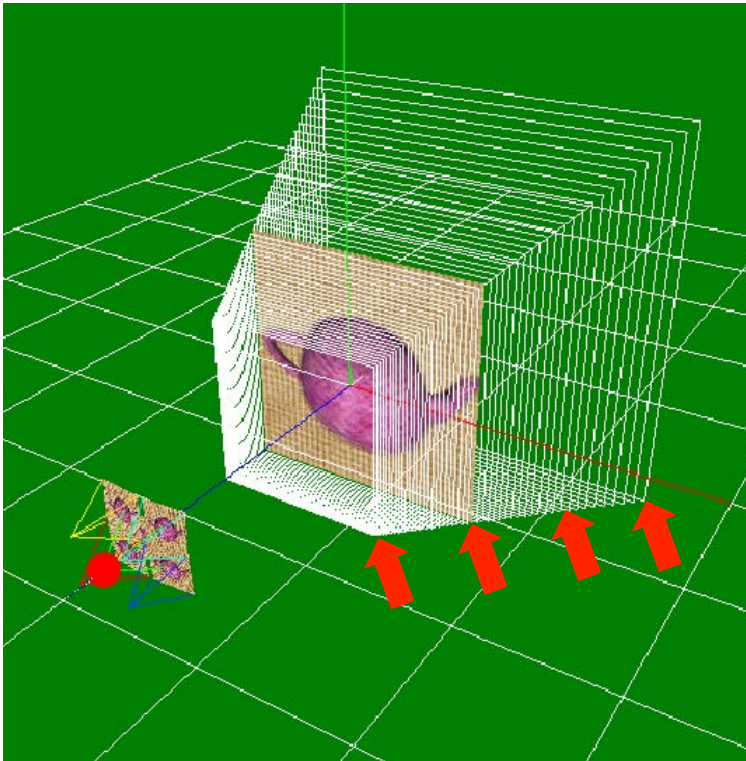
Interesting option to use vertical orientation ([Fraundorfer et al. ECCV2010](#)) or vehicle motion ([Scaramuzza et al. ICCV2009](#)) to facilitate motion estimation



Dense multi-view matching

- Plane-sweep multi-view depth estimation on GPU

(Yang & Pollefeys, CVPR'03)



Blend:

$$(I_0 + I_1 + I_2 + I_3 + I_4) / 5$$

(correct depth=in focus)



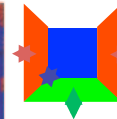
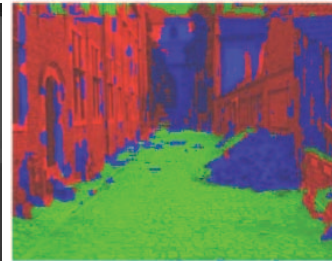
Sum of Absolute Differences:

$$|I_1 - I_0| + |I_2 - I_0| + |I_3 - I_0| + |I_4 - I_0|$$

(correct depth=small value
=dark)

Dense 3D surface reconstruction

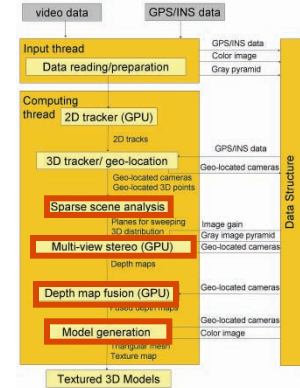
- Multi-Directional plane-sweeping stereo
(Gallup et al., CVPR07)
 - Sweep along façade & ground-plane directions



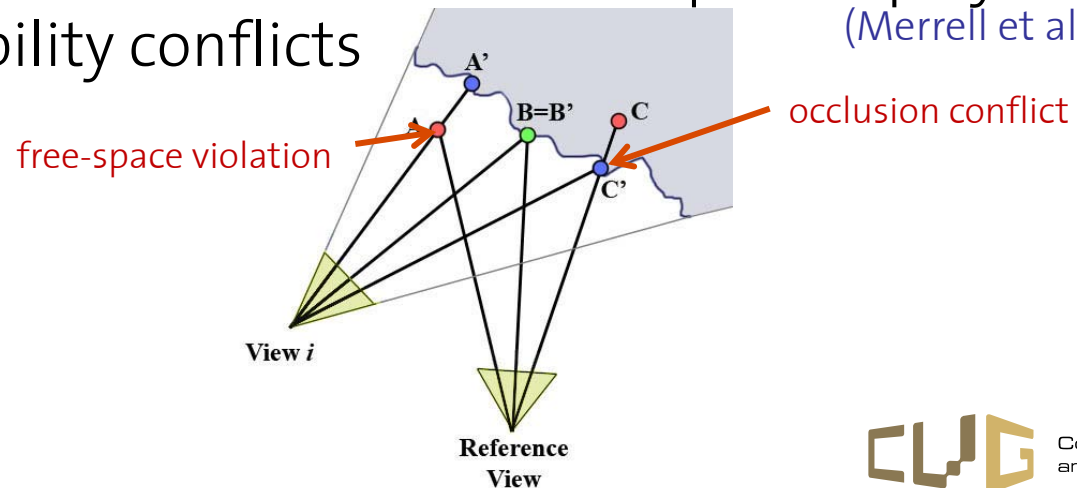
choose best-cost solution over depth and orientation



3D model from 11 video frames (hand-held)



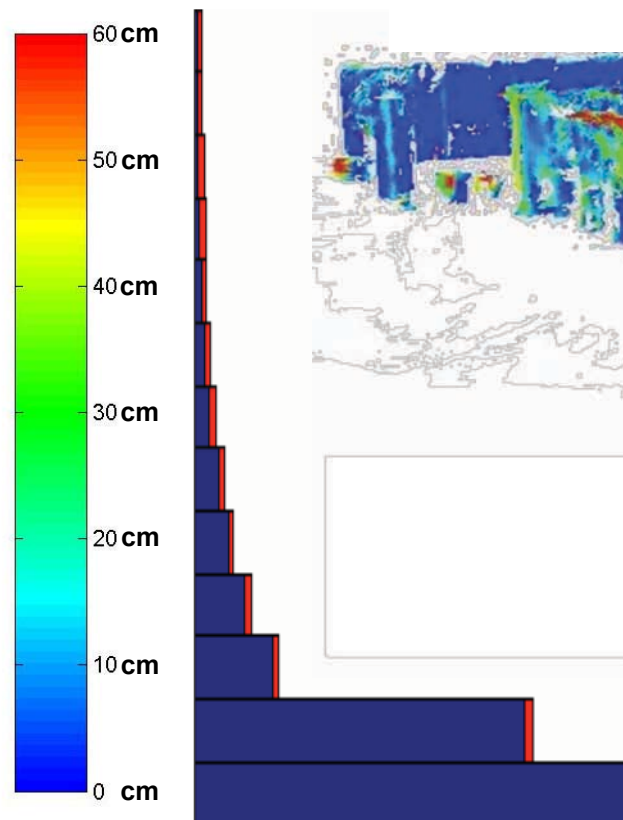
- Fuse depth-maps to obtain consensus depth map by minimizing visibility conflicts
(Merrell et al., ICCV07)



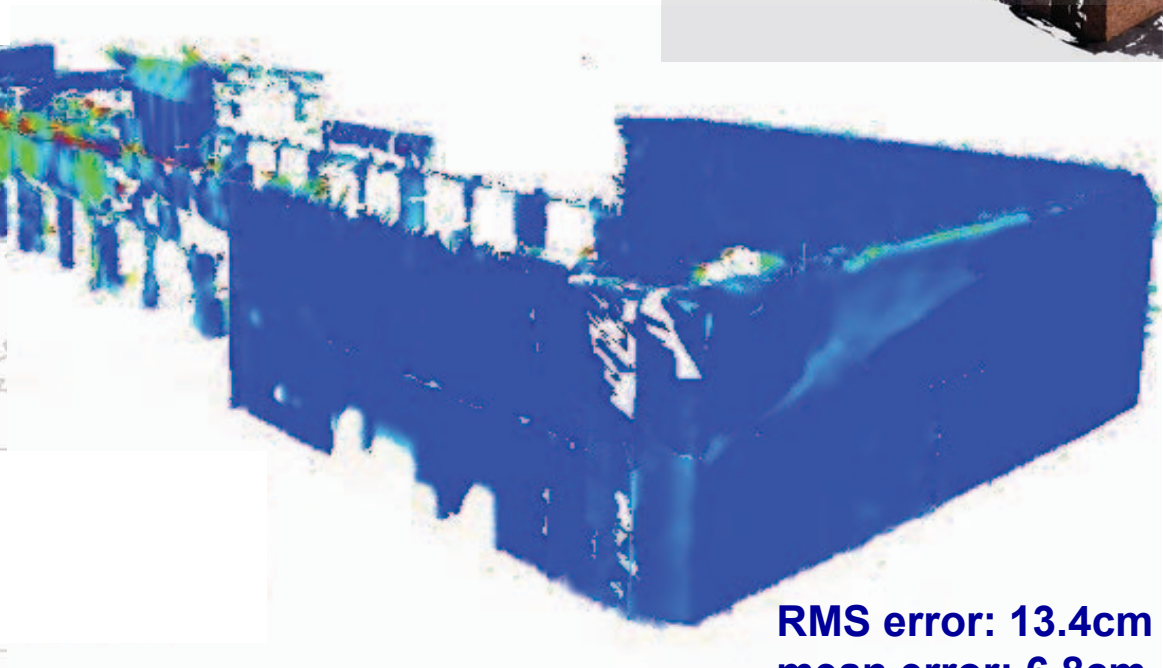
3D-from-video evaluation: Firestone building



building surveyed to 6mm

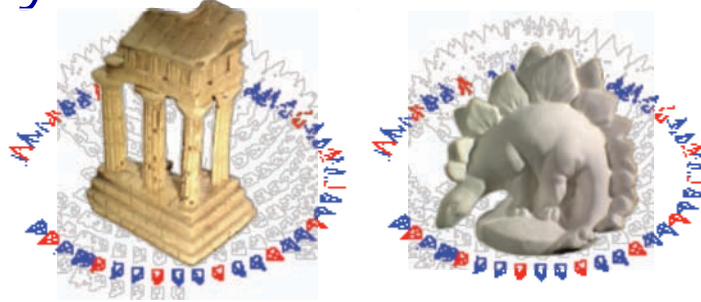


error histogram

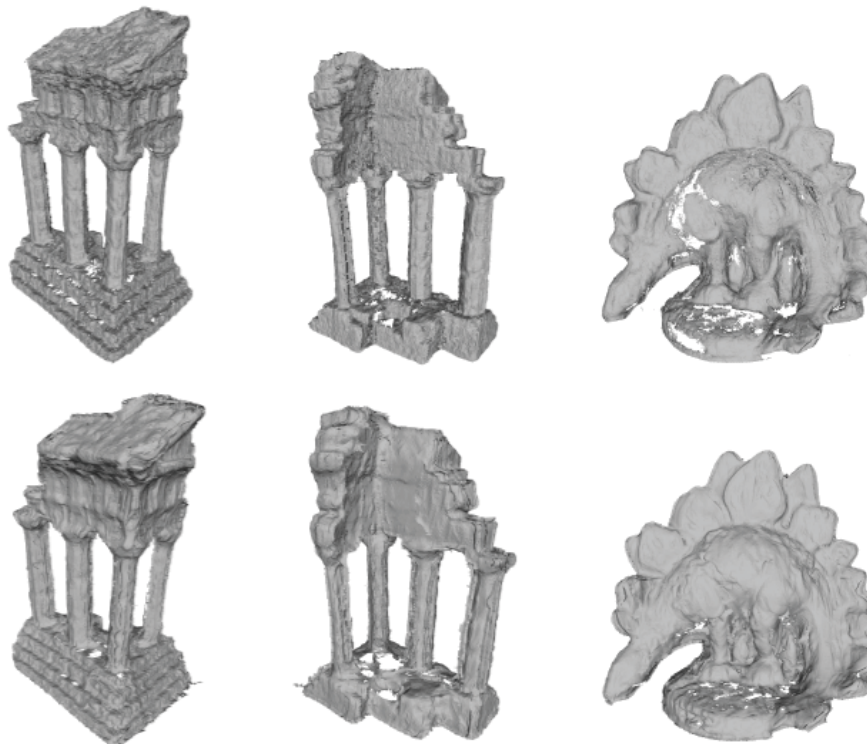


RMS error: 13.4cm
mean error: 6.8cm
median error: 3.0cm

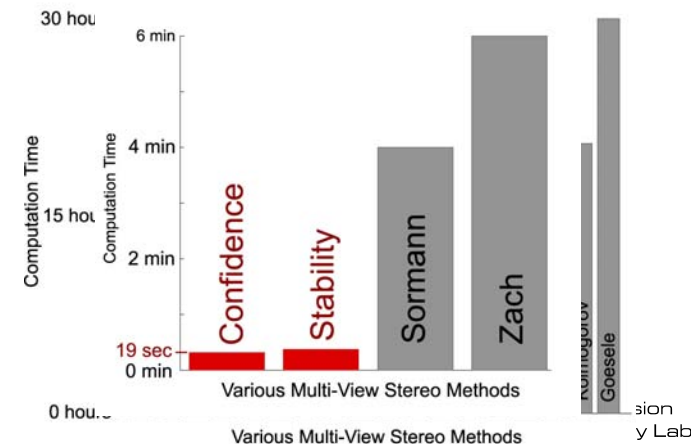
3D-from-video evaluation: Middlebury Multi-View Stereo Evaluation Benchmark



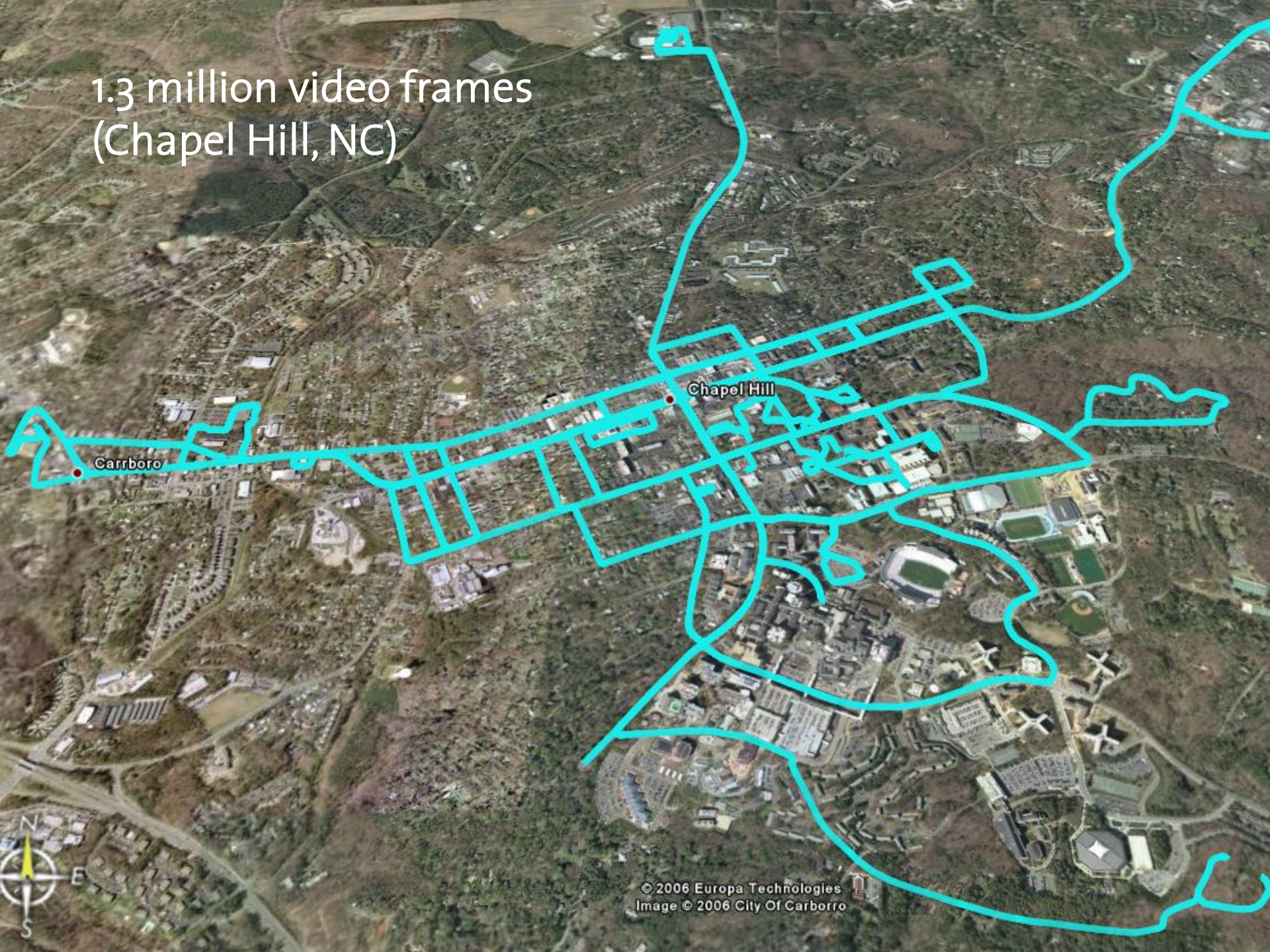
Ring datasets: 47 images



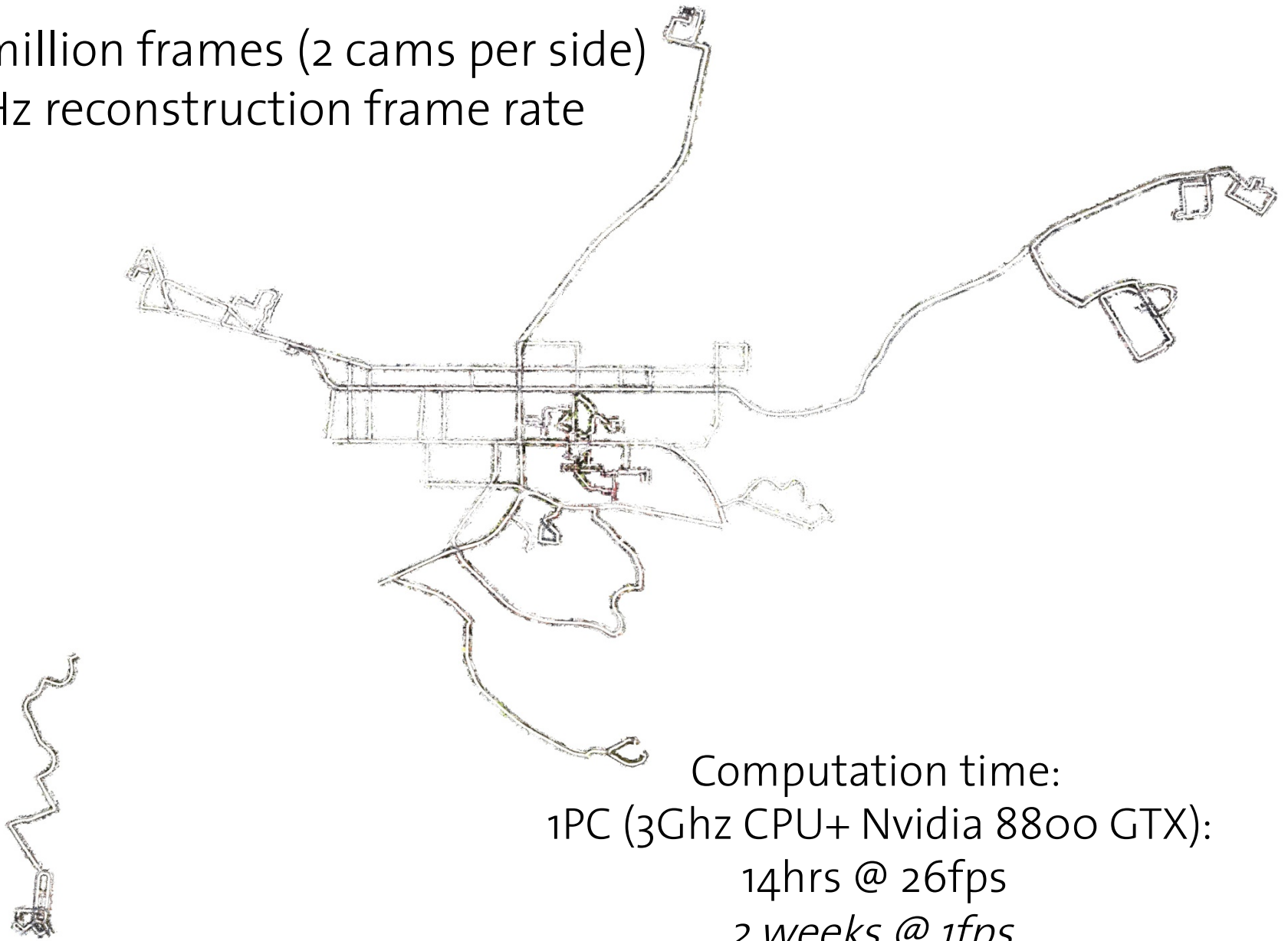
**Results competitive
but much, much faster
(30 minutes → 30 seconds)**



1.3 million video frames
(Chapel Hill, NC)



- 1.3 million frames (2 cams per side)
- 26 Hz reconstruction frame rate



Computation time:

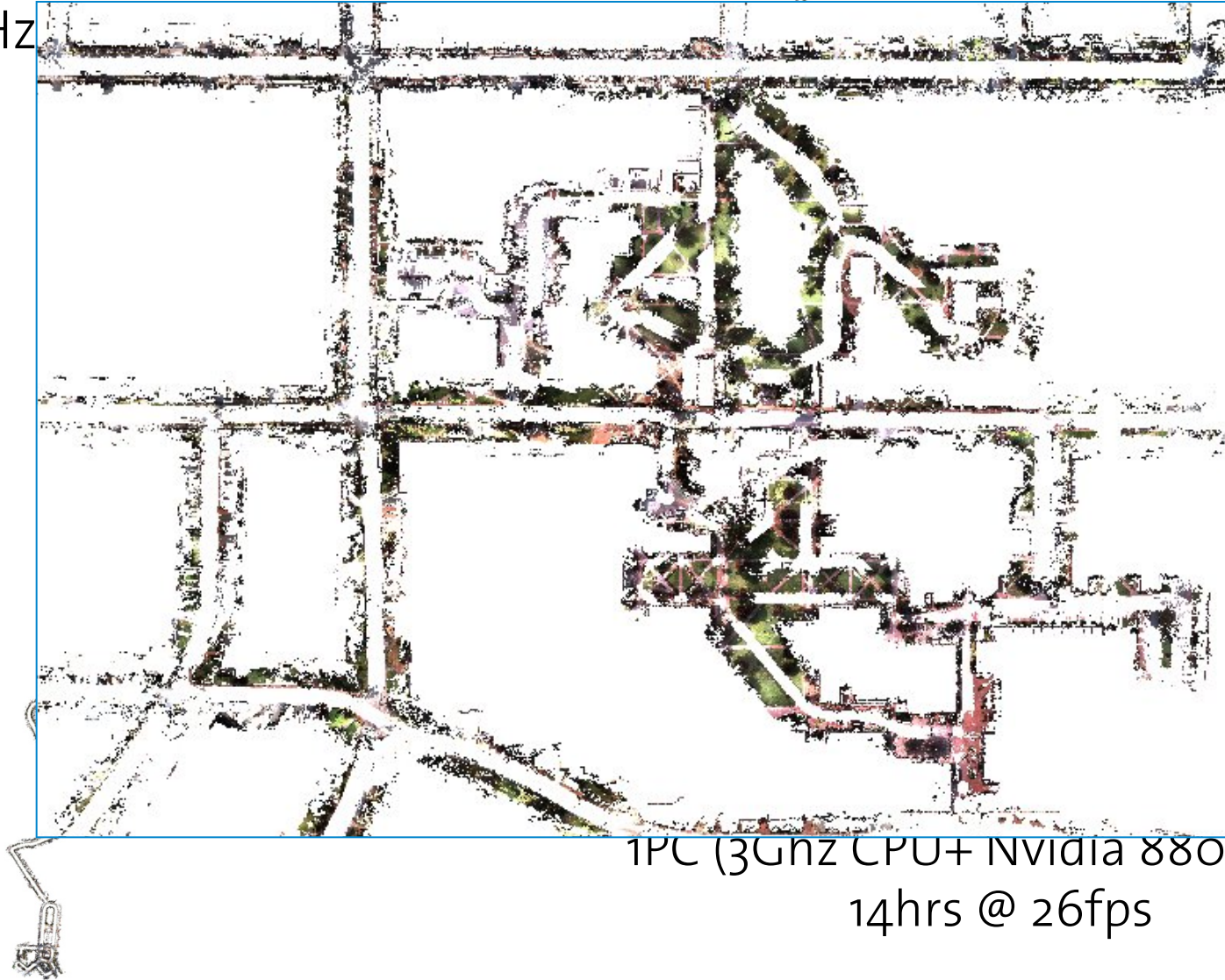
1PC (3Ghz CPU+ Nvidia 8800 GTX):

14hrs @ 26fps

2 weeks @ 1fps

2.5 years @ 1fpm

- 1.3 million frames (2 cams per side)
- 26 Hz



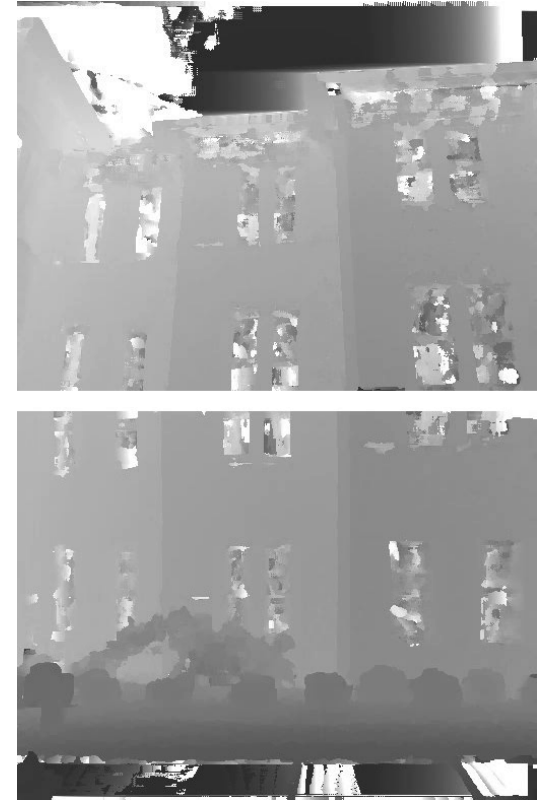
1PC (3GHz CPU+ NVIDIA 8800 GTX):
14hrs @ 26fps

Real-time stereo limitations

Street-Side Video



Real-Time Stereo



Notice problems at windows and homogeneous areas

Including planar prior for urban scenes

(Gallup et al. CVPR10)



Video Frame



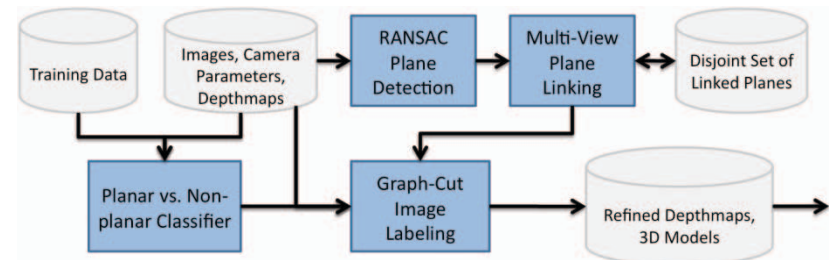
Depthmap with
RANSAC planes



Planar Class
Probability Map



Graph-Cut Labeling



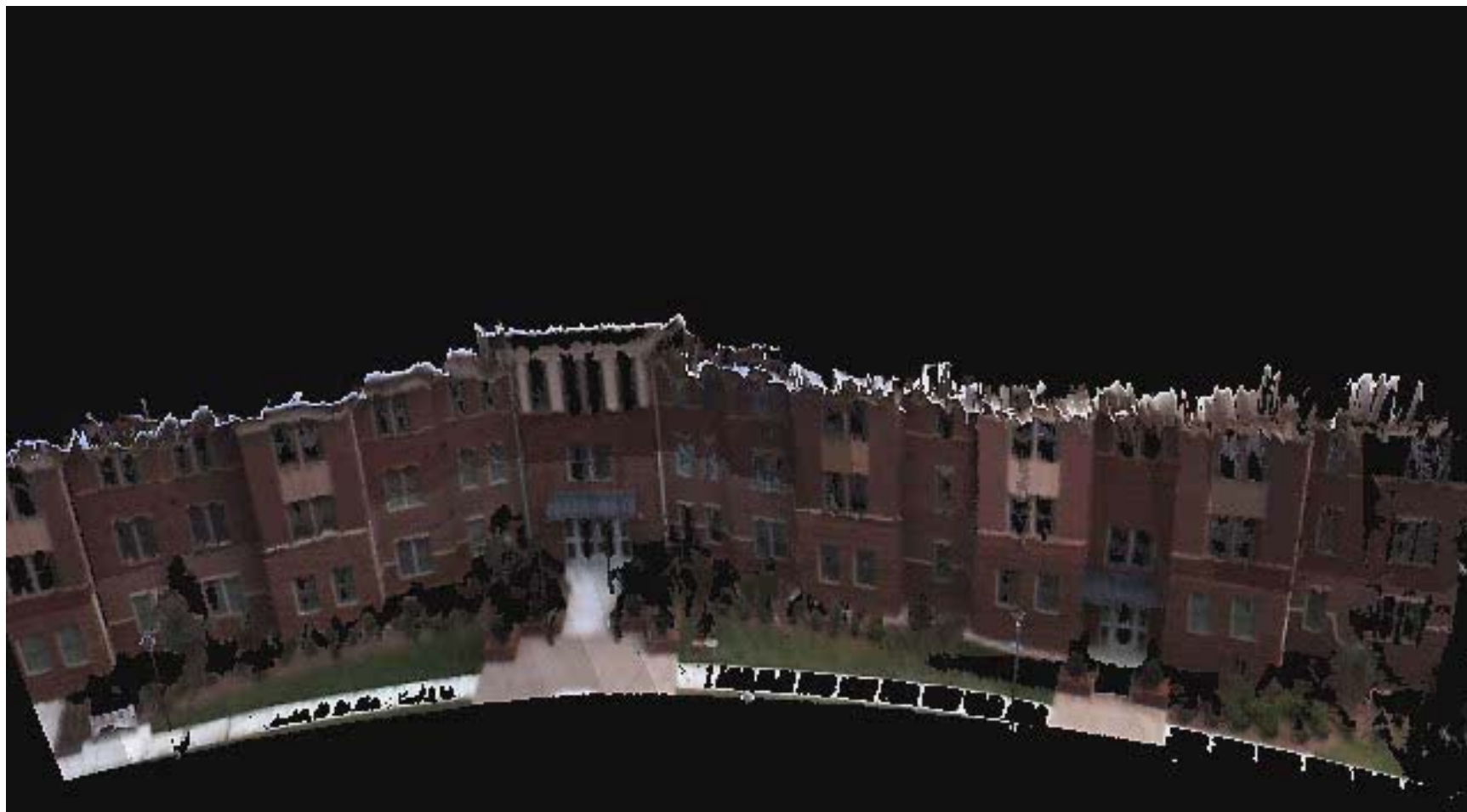
Flowchart



3D Model

Including planar prior for urban scenes

(Gallup et al. CVPR10)



n -layer heightmap fusion

(Gallup et al. DAGM10)



1 Layer



3 Layer



1 Layer



3 Layer



From 2D StreetView to 3D models

(Gallup et al. DAGM10)



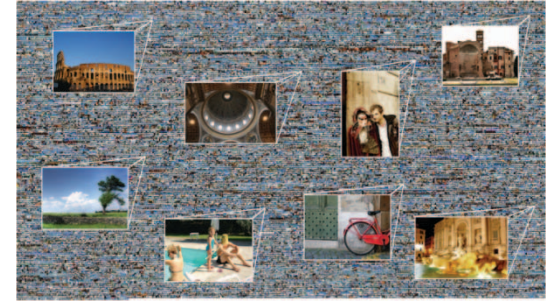
Real-time processing of video (30fps on PC, leveraging GPU)



24

Computer Vision
and Geometry Lab

Building Rome on a cloudless day



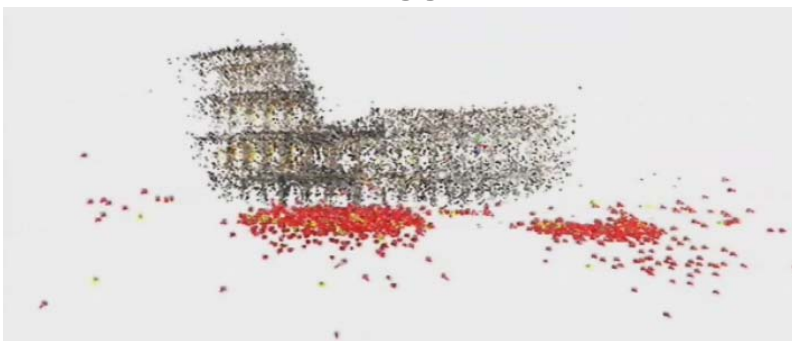
GIST & clustering (1h35)



SIFT & Geometric verification (11h36)



SfM & Bundle (8h35)



(Frahm et al. ECCV 2010)

Dense Reconstruction (1h58)



Some numbers

- 1PC
- 2.88M images (650GB)
- 100k clusters (GIST: 4GB/176MB)
- 22k SfM with 307k images
- 63k 3D models
- Largest model 5700 images
- Total time 23h53

for comparison: Argawal'09 only 150k images/64PC/24h



Computer Vision
and Geometry Lab

Building Rome on a cloudless day

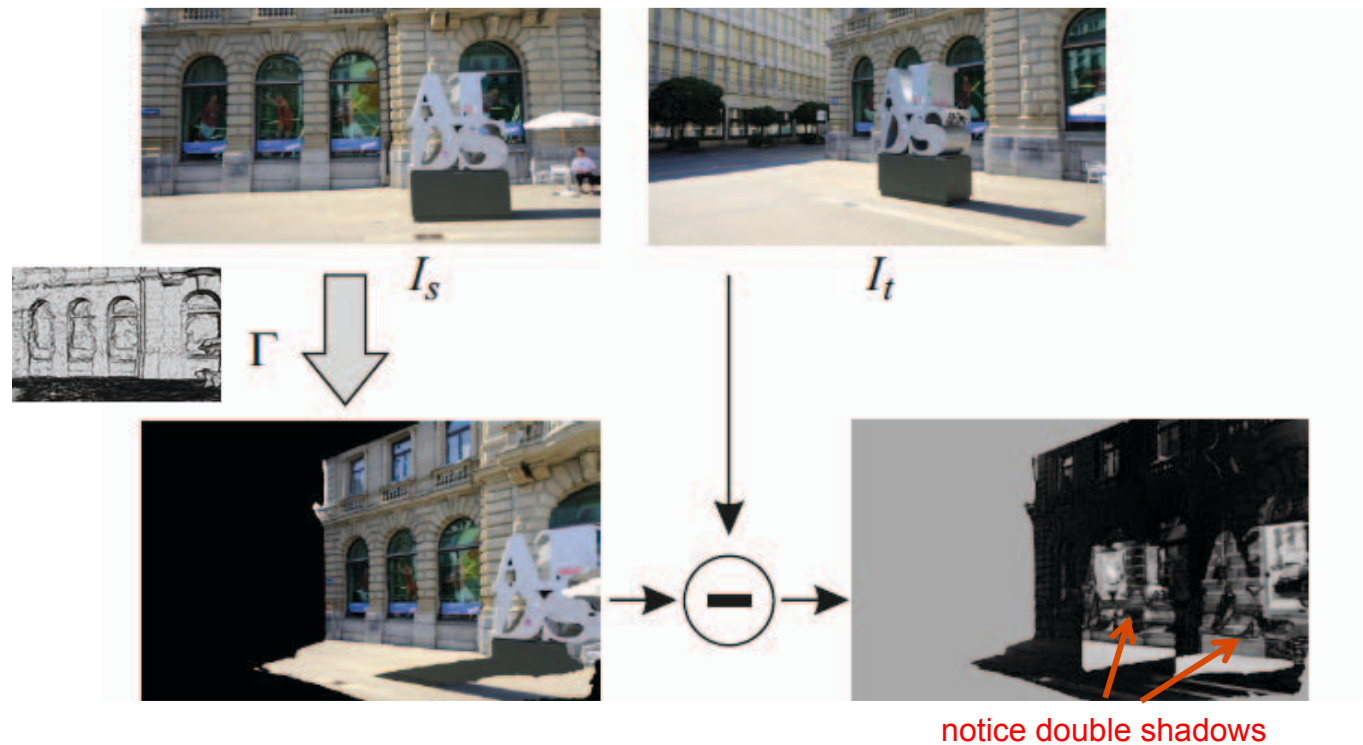
(Frahm et al. ECCV 2010)



Appearance-invariant change detection

(Taneja et al. ICCV2011)

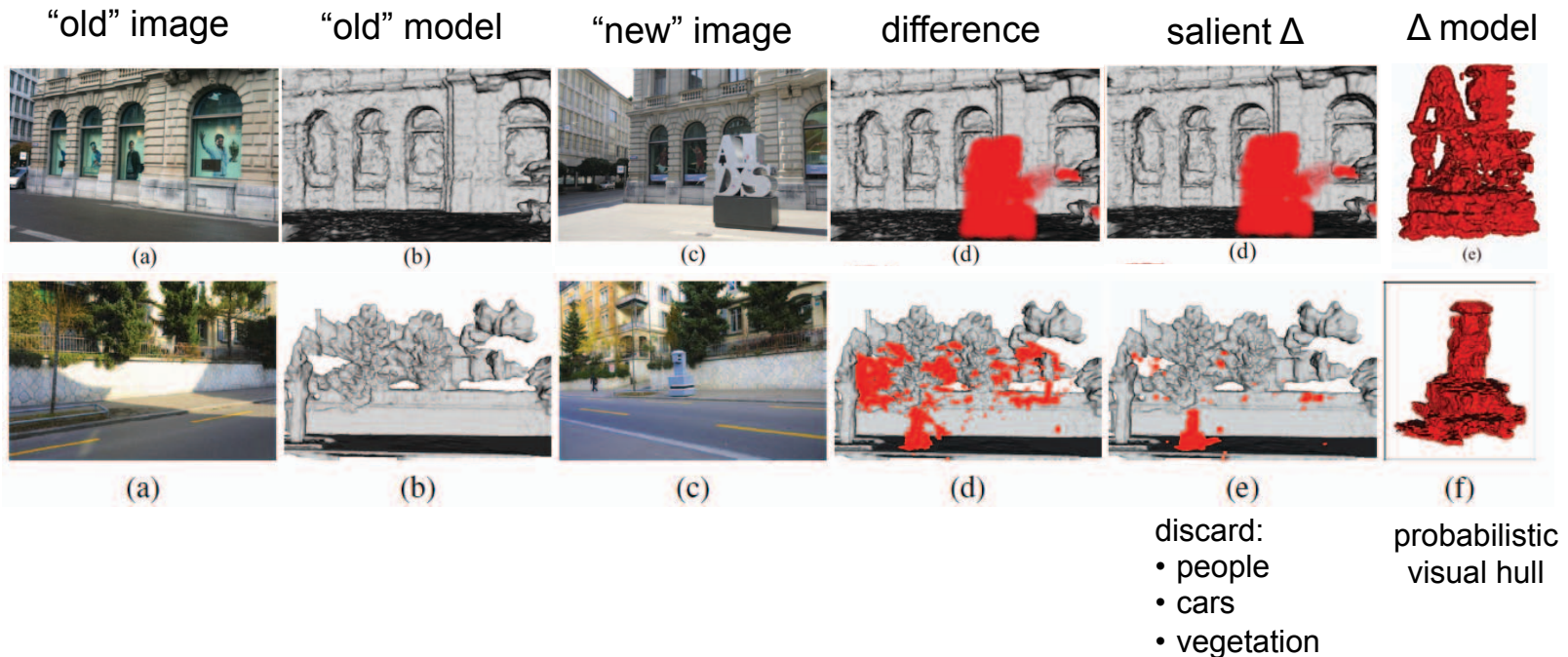
- Estimate pose between “old” model and “new” images
- Transfer and compare “new” images by warping according to “old” model



notice double shadows

Appearance-invariant change detection

(Taneja et al. ICCV2011)



Video-only large-scale reconstruction?

Challenge:

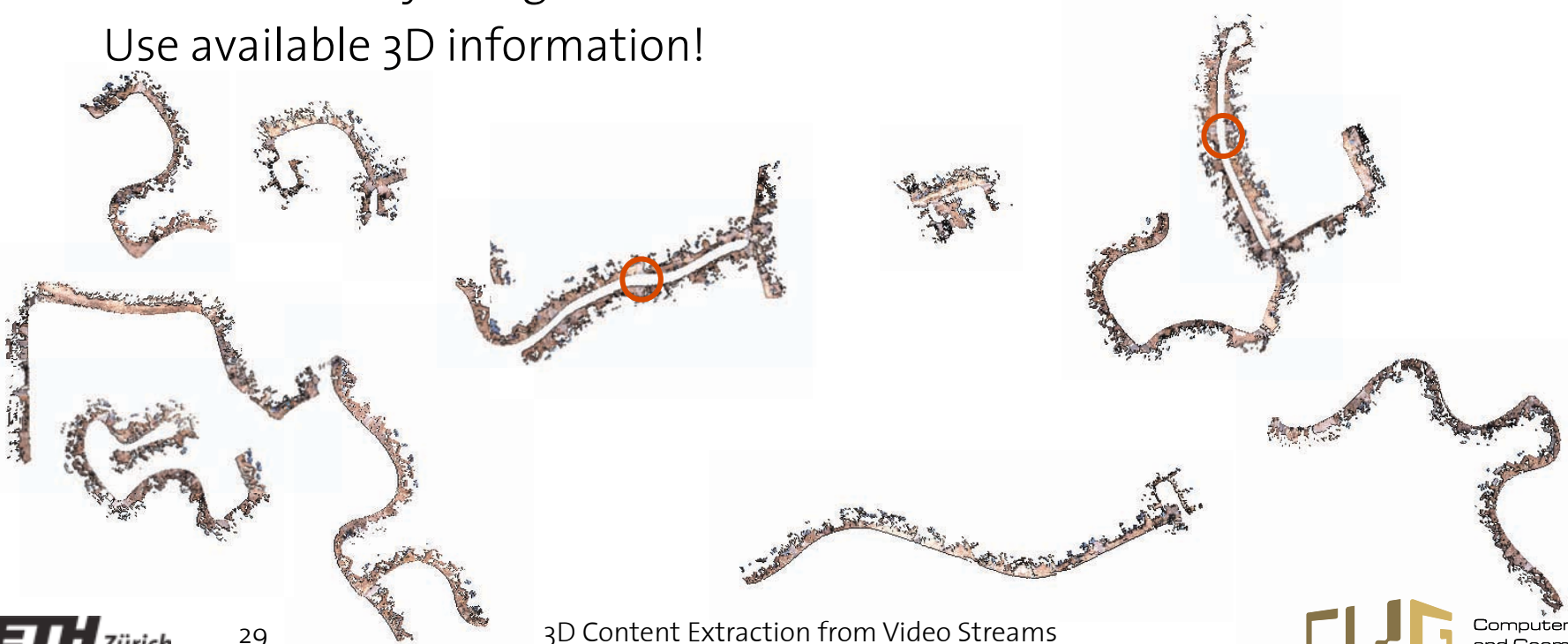
Error accumulation yields drift of relative scale, orientation and position

Solution:

Cancel drift by closing loops (e.g. at intersections)

Need to visually recognize locations

Use available 3D information!



Matching video segments/3D models

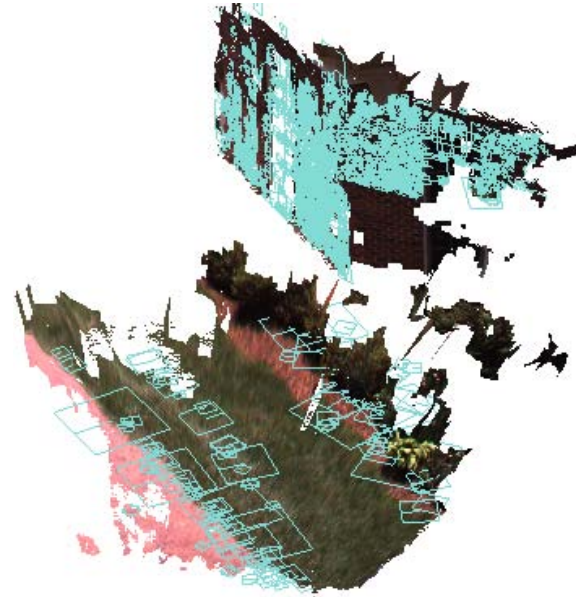
SIFT features

- Extracted from 2D images
- Variation due to viewpoint



VIP features (Wu et al., CVPR08)

- Extracted from 3D model
- Viewpoint invariant



3D Models with VIPs



Geo-location from images

(Batz et al., ECCV2010;
Chen et al. CVPR 2011)

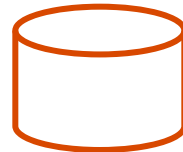
Images + 3D Database



Building ortho-textures



descriptor
database



Rectification of query image

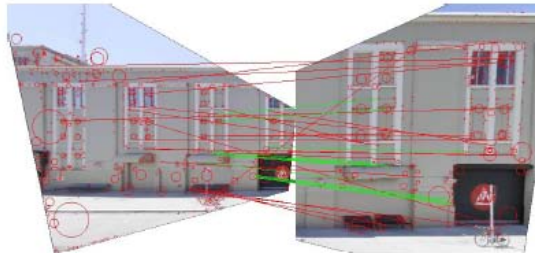


rectified features

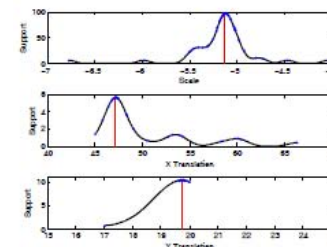
promising
candidates



Geometric verification



Computational 3D Photography



scale

x translation

Collaboration with **NOKIA**
Connecting People

Minimal relative pose with know vertical

(Fraundorfer et al., ECCV2010)



Vertical direction can often be estimated

- inertial sensor
- vanishing point

$$E = \begin{bmatrix} t_z \sin(y) & -t_z \cos(y) & t_y \\ t_z \cos(y) & t_z \sin(y) & -t_x \\ -t_y \cos(y) - t_x \sin(y) & t_x \cos(y) - t_y \sin(y) & 0 \end{bmatrix}$$

5 linear unknowns → linear 5 point algorithm

3 unknowns → quartic 3 point algorithm

Challenge: repetition ambiguity



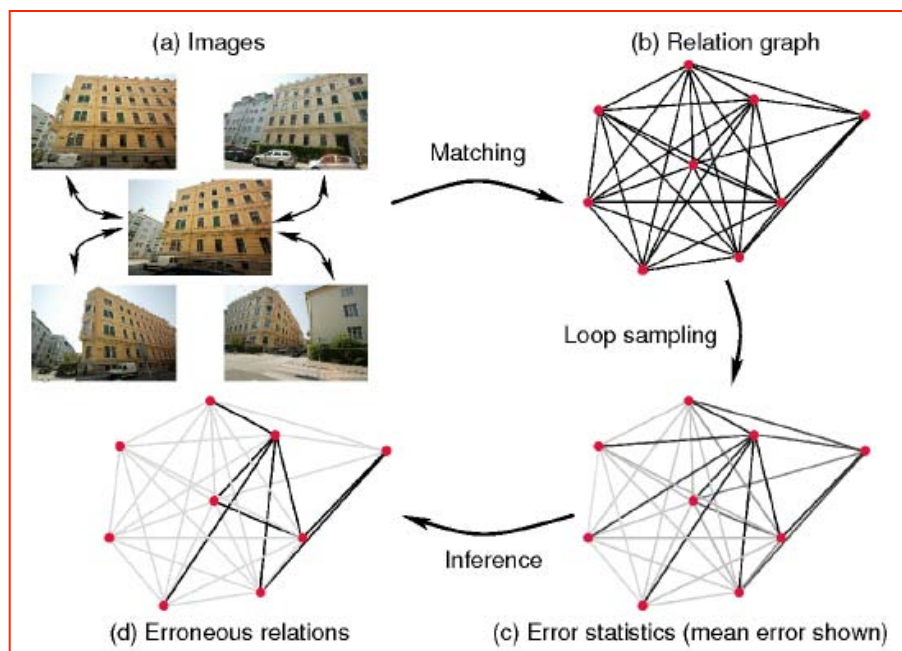
(a) Unrelated images, 228 matches



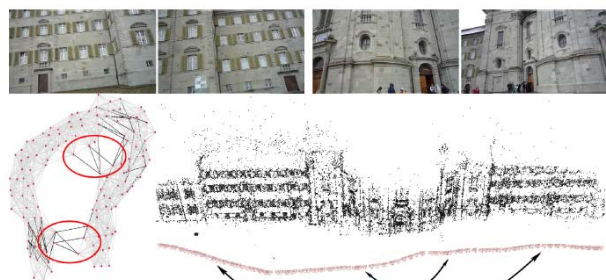
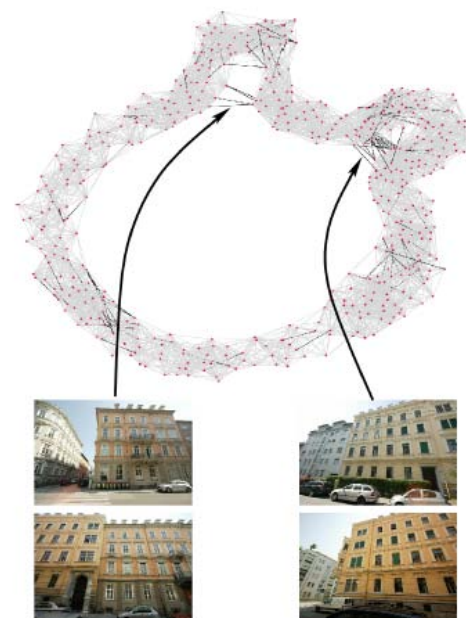
(b) Snapped to the wrong repetition, 331 matches

→ result in incorrect correspondences !

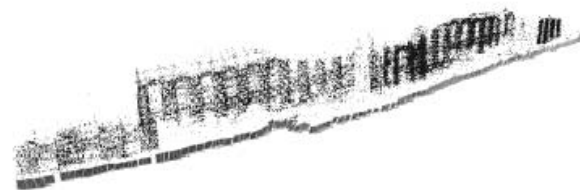
Disambiguating visual relations using loop constraints



(Zach et al CVPR'10)



(a) W/o edge filtering (143 views registered)



(b) With edge filtering (all 189 views registered)

Dense reconstruction from symmetry

(Koeser et al DAGM'11)
recipient DAGM main prize)

- Detect symmetry and perform dense matching



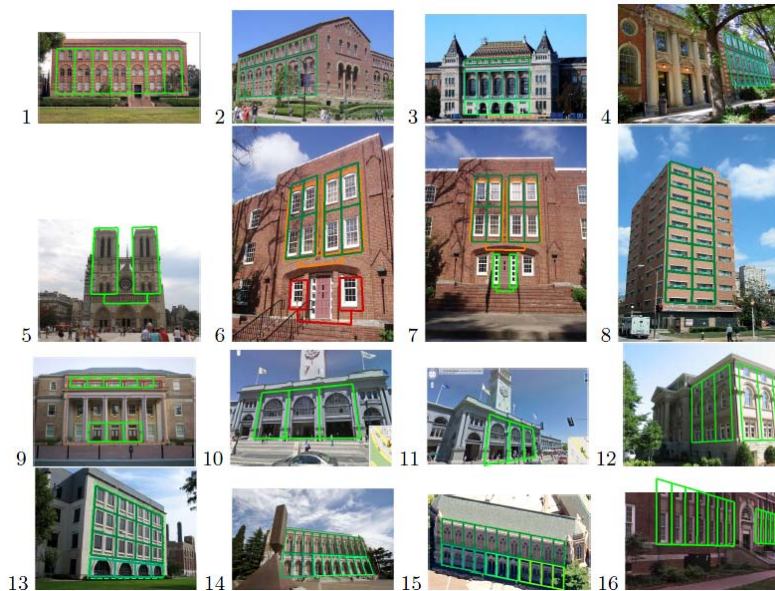
more examples:

<http://tinyurl.com/depthfromsymmetry>



Towards Parsing Urban Scenes

- Detecting symmetries and repetitions (Wu et al ECCV'10)



- Applications:
 - Extracting architectural grammars
 - Matching repeating structures
 - Shape from symmetry and repetition (Wu et al CVPR11)



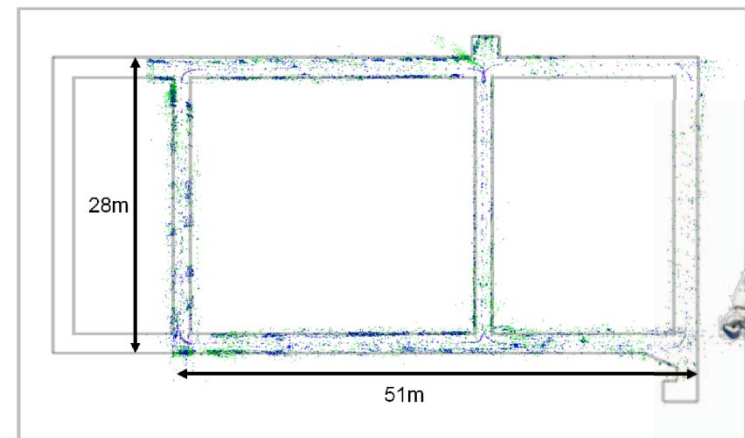
Real-Time Stereo Visual SLAM

(Clipp et al., IROS2010;
Lim et al., CVPR2011)

- Stereo KLT for local motion estimation
- SIFT for feature redetection and loop closure
- Local and global bundle adjustment

Parallel, Real-Time VSLAM

IROS 2010



Collaboration with **HONDA**
The Power of Dreams

Marc Pollefeys

Real-Time Stereo Visual SLAM

(Lim et al., CVPR2011)

Online Environment Mapping

Supplementary Video

Paper ID: #828



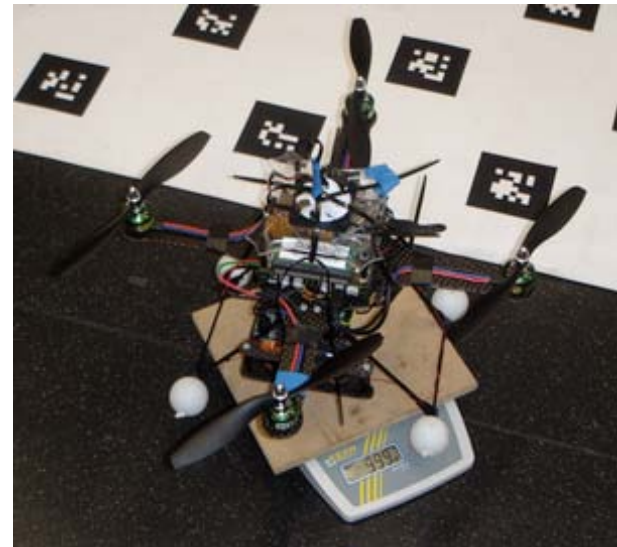
More applications of SLAM

OmniTour

(Saurer et al., 3DPVT2010)



MAVs



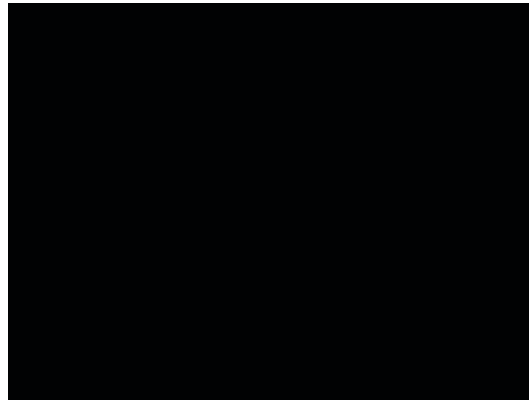
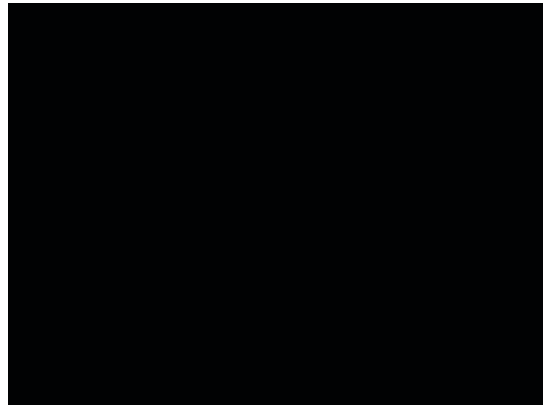
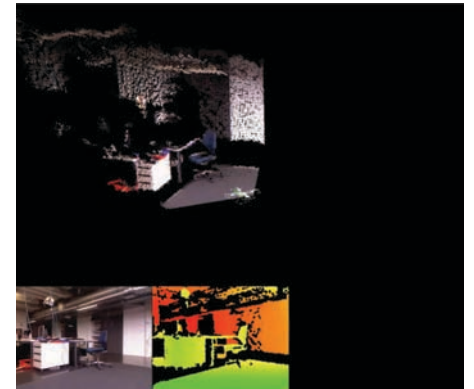
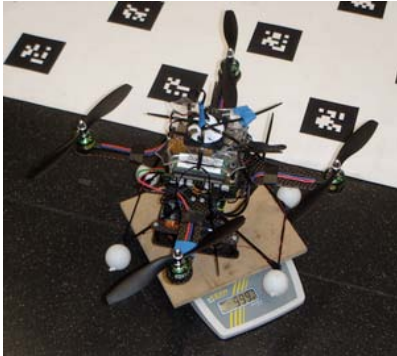
PixHawk student team
1st place autonomy EMAVog
(<http://pixhawk.ethz.ch/>)

Funded with  ward

Autonomous micro-helicopter navigation

(Meyer et al. ICRA11; Heng et al. ICRA11; Lee et al. ICRA11; Heng IROS11,...)

Student build MAV platform
developed for vision-based control



More on PixHawk: <http://pixhawk.ethz.ch>



Computer Vision
and Geometry Lab

OmniTour

(Saurer et al., 3DPVT2010)



Immersive tour building tool

- Omnidirectional video
- Approximate SfM
- Interactive map alignment

OmniTour

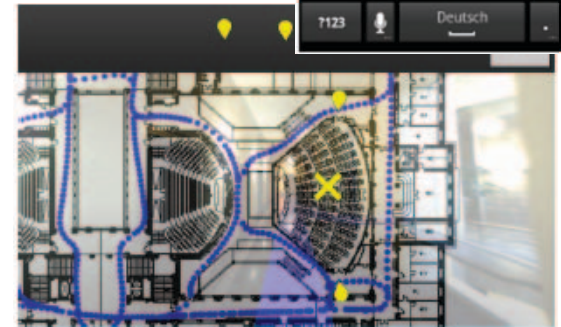
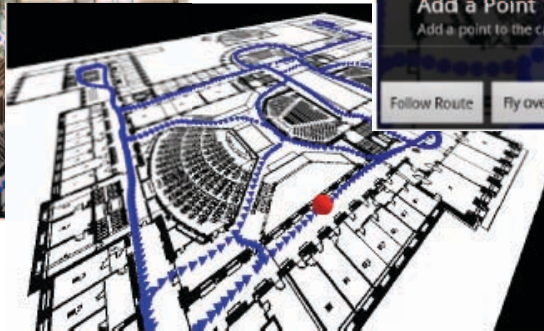
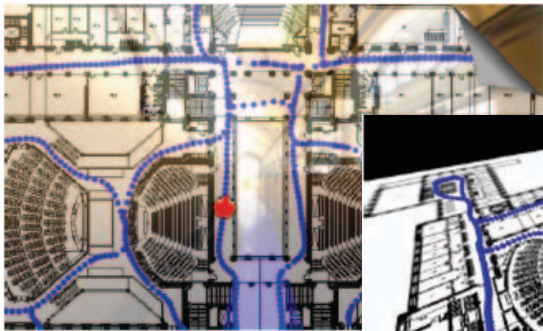
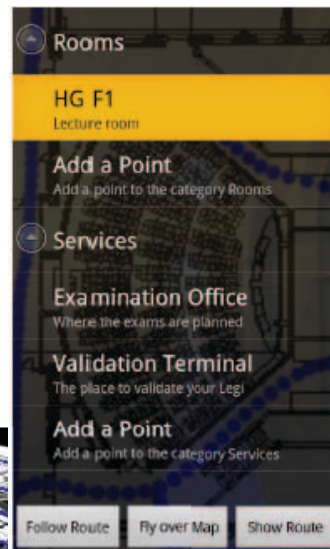
(Saurer et al., 3DPVT2010)

Authoring Tool

MobileTour

Schmid'11 (BS thesis)

Android application for exploration, navigation, editing POI



Also work on indoor mobile localization

Waldin'11 (BS thesis)

MobileTour

Schmid'11 (BS thesis)



Also work on indoor mobile localization

Waldin'11 (BS thesis)

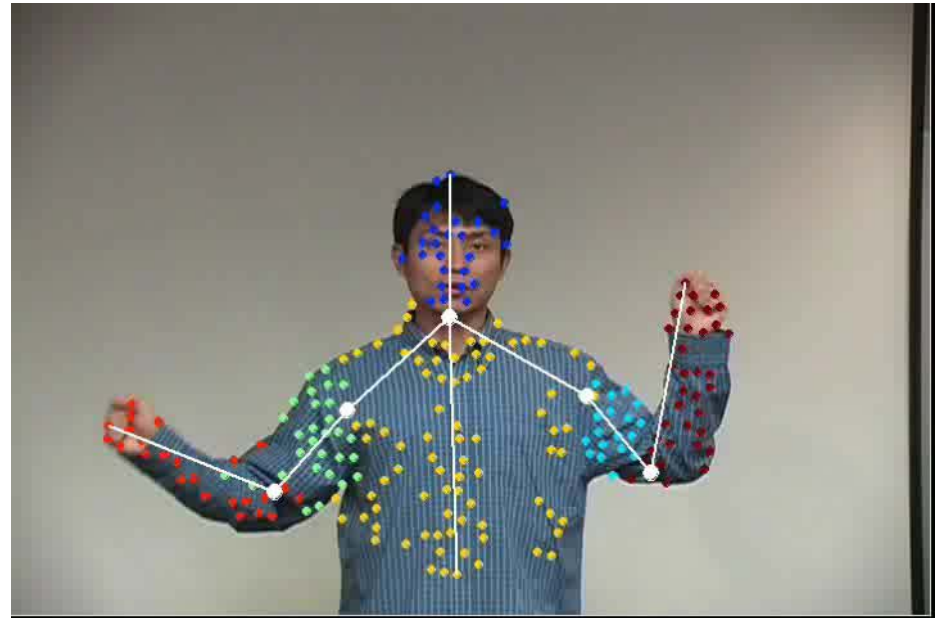
Talk outline

- Introduction
- Object modeling
- Scene modeling
- People/event modeling
- Summary and conclusion

Monocular Articulated Motion and Shape Recovery

(Yan & Pollefeys, CVPR05/ECCV06/CVPR06 & PAMI08)

- Feature tracks of articulated bodies span multiple intersecting 4D linear subspaces (under affine imaging conditions)
- Motion segmentation using local subspace affinity
 - Best in recent comparison (Tron & Vidal, CVPR07)
- Kinematic chain recovery
- Articulated 3D motion and shape recovery



Multi-Camera Factorizations

(Angst & Pollefeys ICCV09/ECCV10)

- (Static) affine cameras
- Rigidly moving object
- Camera calibration using rigid motion
 - 2D feature point trajectories as input
 - No feature point correspondences between different camera views required

juxtapose x, y coordinates
for all points and cameras

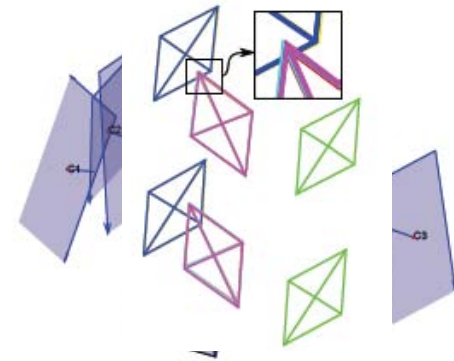
for all frames

$$\begin{bmatrix} x_{11}^1 & y_{11}^1 & x_{12}^1 & y_{12}^1 & x_{13}^1 & y_{13}^1 & \cdots \\ x_{21}^1 & y_{21}^1 & x_{22}^1 & y_{22}^1 & x_{23}^1 & y_{23}^1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1}^1 & y_{m1}^1 & x_{m1}^1 & y_{m1}^1 & x_{m1}^1 & y_{m1}^1 & \cdots \end{bmatrix}$$

rank ≤ 13

all tracks of all affine cameras form rank 13 subspace!

(for planar motion only rank 5)



Multi-Camera Factorizations

(Angst & Pollefeys ICCV09/ECCV10)

- Image coordinate
 - affine projection onto a camera axis (trilinear)

$$\mathbf{x}_{t,k,n} = \mathbf{C}_k \mathbf{M}_t \mathbf{S}_n \quad \text{e.g.} \quad \begin{bmatrix} u \end{bmatrix} = \underbrace{\begin{bmatrix} r_{11} & r_{12} & r_{13} \end{bmatrix}}_{\text{camera pose}} \underbrace{\begin{bmatrix} \mathbf{R} & \mathbf{t} \\ 0_3 & 1 \end{bmatrix}}_{\text{object motion}} \underbrace{\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}}_{\text{object shape}}$$

- Stack observations in matrix

$$\begin{aligned} \mathbf{W} &= [\Downarrow_{t \Rightarrow k \Rightarrow n} \mathbf{x}_{t,k,n}] = [\Downarrow_{t \Rightarrow n, k} (\text{vec}(\mathbf{M}_t))^T (\mathbf{S}_n \otimes \mathbf{C}_k^T)] \\ &= \underbrace{[\Downarrow_t (\text{vec}(\mathbf{M}_t))^T]}_{T \times 16} \underbrace{[[\Rightarrow_n \mathbf{S}_n] \otimes [\Rightarrow_k \mathbf{C}_k^T]]}_{16 \times 2KN} = \mathbf{AB} \end{aligned}$$



general motion: rank 13
planar motion: rank 5

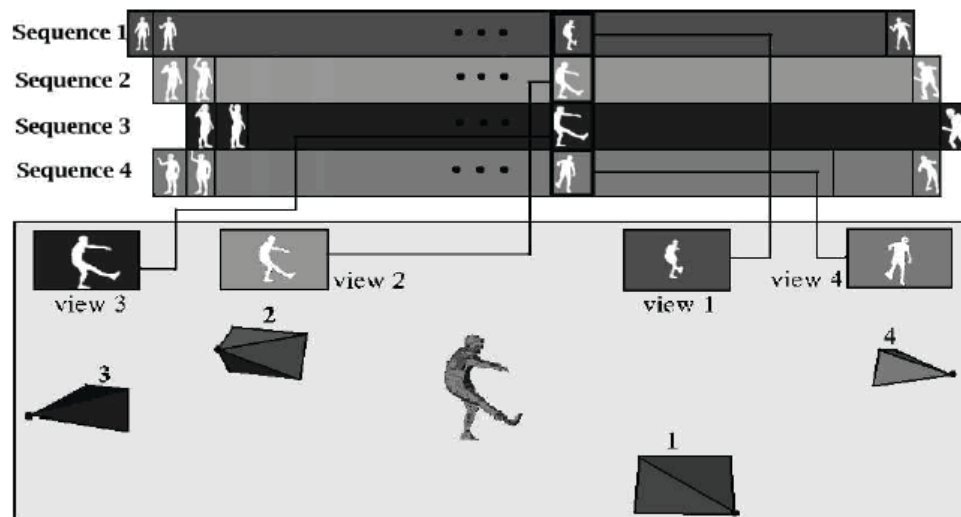
$$\mathbf{T}_{\text{planar}} = \begin{bmatrix} \cos \theta & \sin \theta & 0 & a \\ -\sin \theta & \cos \theta & 0 & b \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Camera network calibration from silhouettes

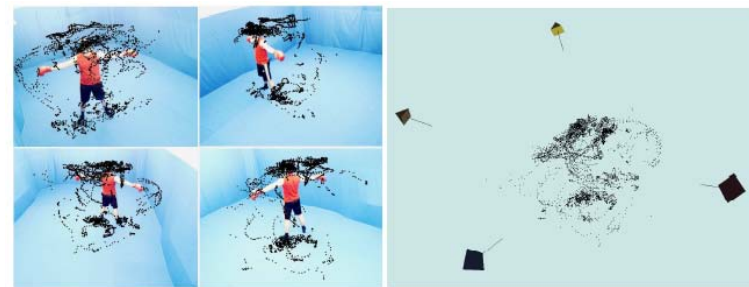
(Sinha et al., CVPR04; Sinha and Pollefeys IJCV10)



4 minutes of video from 4 camcorders (recorded at MIT)

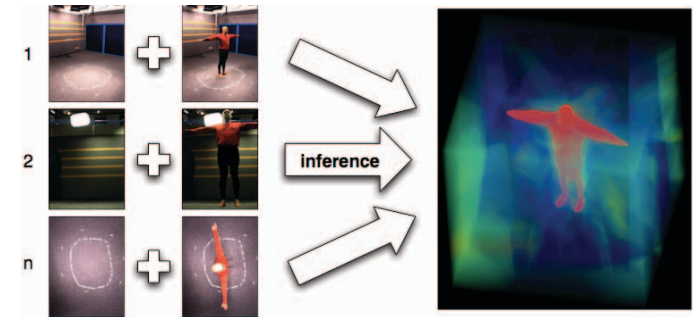


calibrate –and synchronize– camera network
without requiring specific calibration data
Our approach is robust and efficient



<http://cs.unc.edu/~ssinha/Research/silcalib/>

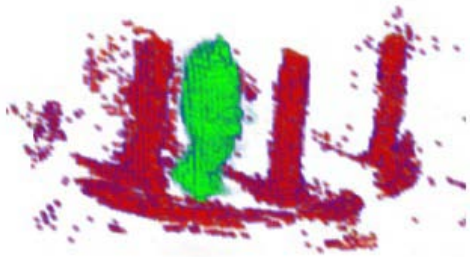
Probabilistic occupancy from silhouettes



(Franco and Boyer, ICCV05)

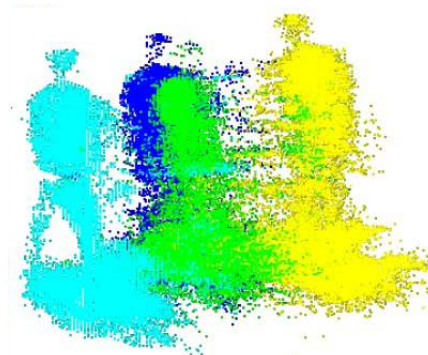
Occluder modeling

(Guan et al. CVPR07)



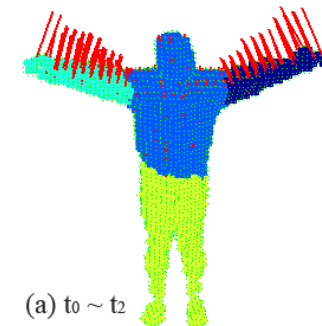
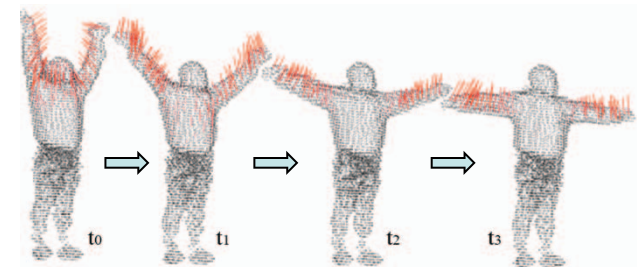
multi-person

(Guan et al. CVPR08)



Occupancy flow

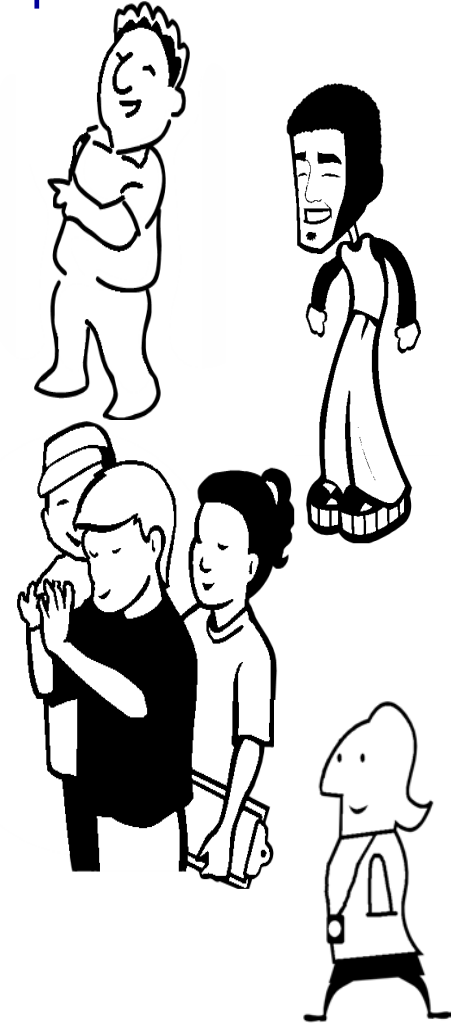
(Guan et al. CVPR10)



Interactive Navigation of casually captured videos



Collection of videos
of the same event
from different angles



Crowd of people
(with cameras)

Interactive Navigation of casually captured videos



Navigation in space and time

Casually Captured Videos



- Only few assumptions on the scene
- Large uncontrolled environments
- Filmed by nonprofessional people

How can we perform VBR in such a scenario?

Our Proposed System

(Ballan et al. SIGGRAPH10)



Video collection



Offline
Processing



Navigation
System

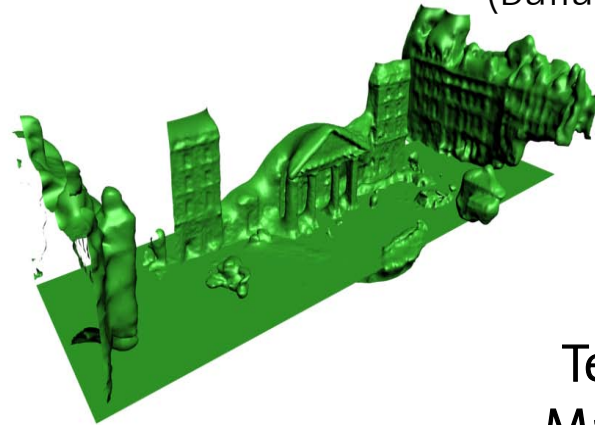


Offline Processing

(Ballan et al. SIGGRAPH10)



3D modeling



Texture
Mapping



Collection of images
of the filming location

Offline Processing

(Ballan et al. SIGGRAPH10)



Video collection

Offline Processing

(Ballan et al. SIGGRAPH10)

Color calibration



Video collection

Time Synchronization



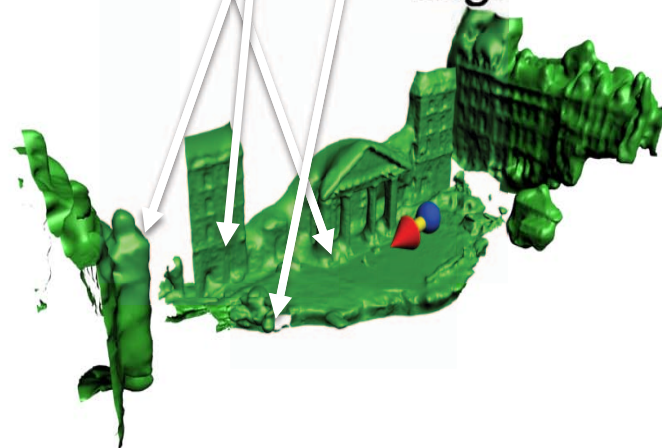
Spatial Calibration of the Videos

(Ballan et al. SIGGRAPH10)

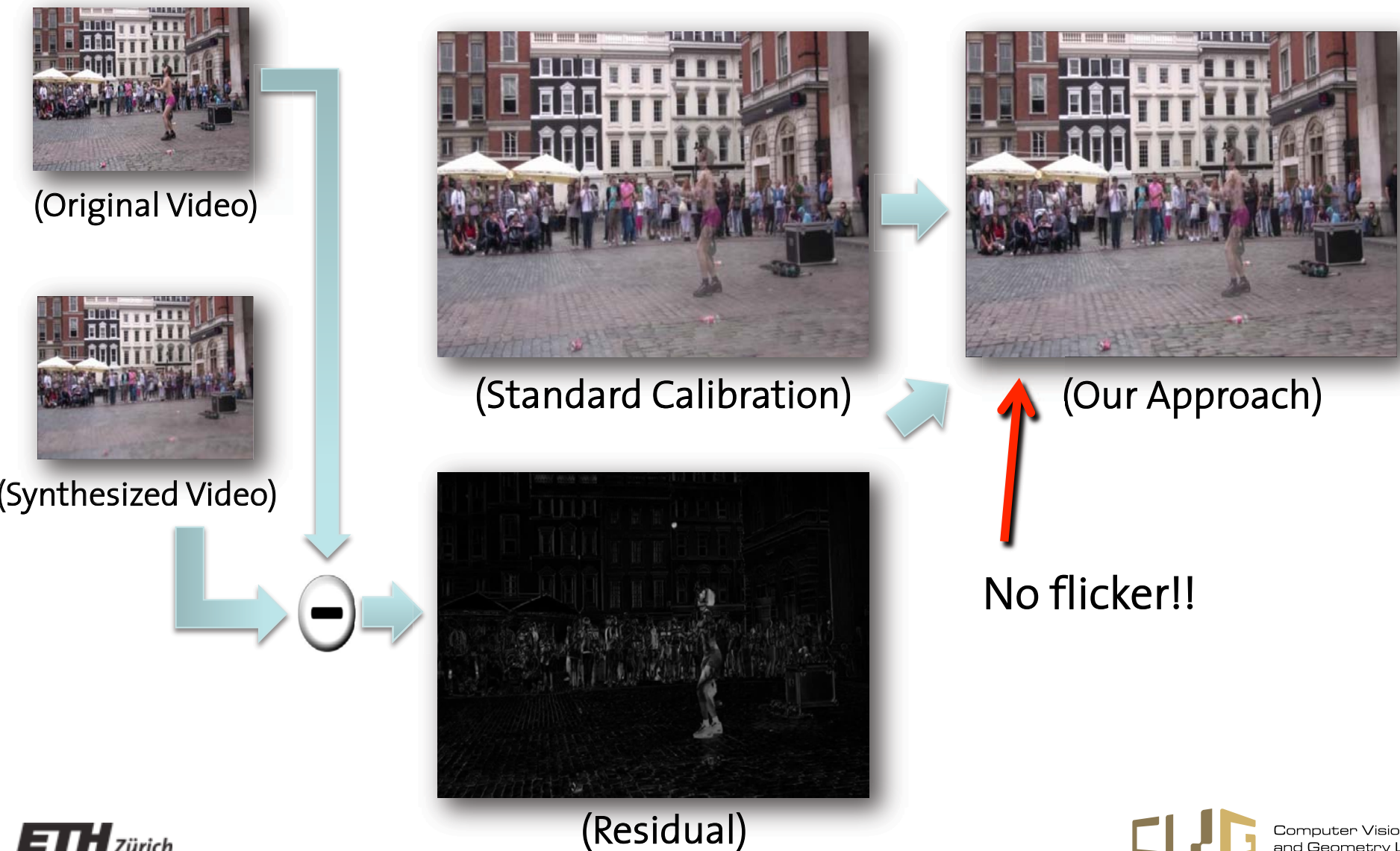


Collection of images

Compute camera pose
for every camera
at every instant



Spatial Calibration of the Videos



Performer Segmentation

(Ballan et al. SIGGRAPH10)



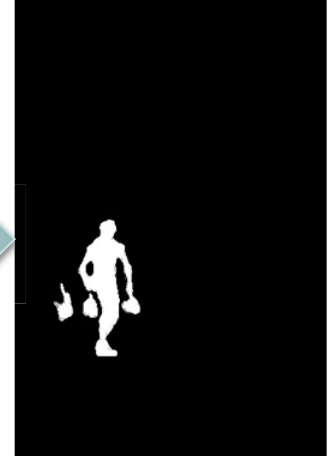
Input
video



Color
based
segment
ation



Per-pixel color model
of the background



Foreground-
background
segmentation

Rendering (interactive, on-line)

Request for a transition

Background

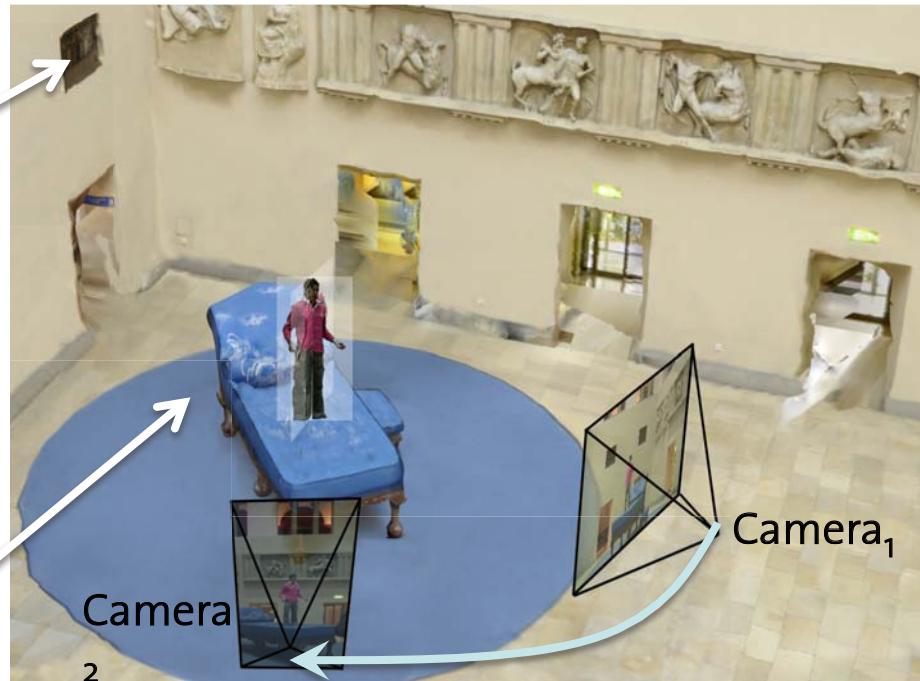


Pre-computed background geometry

Foreground



Billboards



Generate intermediate views along transition path

The Background



ff



Sources

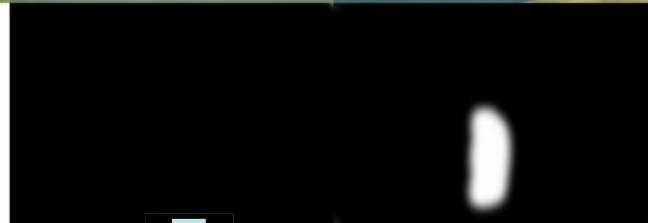
(Camera 1)

(Camera 2)

(Background geometry)



Weights



adapt Unstructured Lumigraph

(Buehler et al.'01)

- Moving cameras
- Mask out the foreground
- Limit to only three sources to maintain real-time

Final rendering



The Inter-Billboard distance



Unoptimized transition
(Naïve approach)



Optimized transition
(Our approach)

Interactive Navigation Tool: UI

(Ballan et al. SIGGRAPH10)



Interactive viewer, more results & datasets available at:

<http://cvg.ethz.ch/research/unstructured-v>



Starting Grant 4D Video



Computer Vision
and Geometry Lab

Conclusion

- Possibility to compute shape, motion and appearance from video, as well as camera system calibration
- Challenges:
 - Large-scale scenes
 - Dynamic objects, people in particular, in cluttered scenes
- Opportunities:
 - Advances in camera, processing, network and storage technologies
 - Lots of interesting applications in many different areas

Thank you for your attention!

Questions?