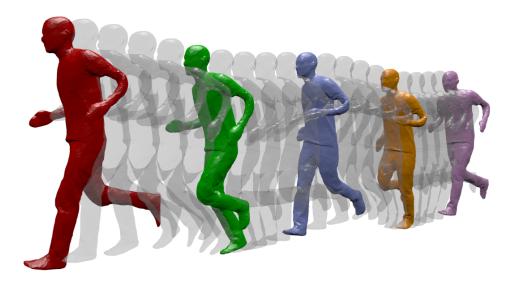




4D Shape Modeling



Edmond Boyer MORPHEO - INRIA Grenoble Rhône-Alpes





- [Computer] Vision: Using visual cues to infer information on the real environment.
- 4D Scene Modeling: analysis of 3D scenes composed of real objects, possibly moving and deforming
 - 1. Shape Modeling: Static->3D, dynamic->4D (3D+t).
 - 2. Motion Modeling.
 - 3. Motion Semantic Modeling (e.g. modeling actions, activities).

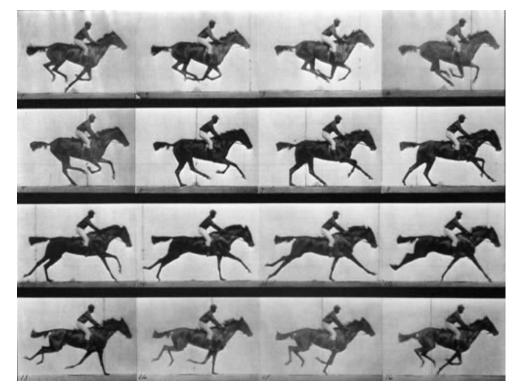
• Applications :

Contents Production: TV3D, Virtual/Augmented Reality, Interactions. Intelligent Environments: smart rooms, Surveillance. Medical applications. Etc.





Early use of visual information to infer moving shape features

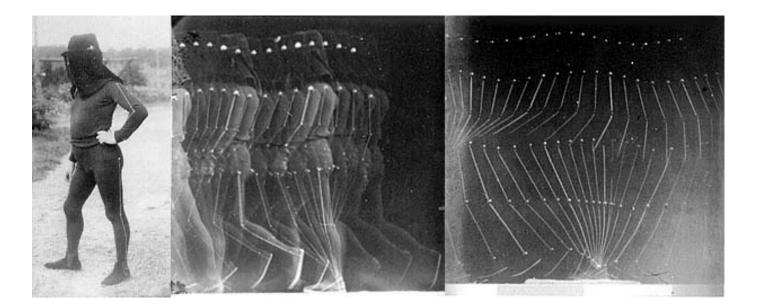


Eadweard Muybridge (1878): Animal locomotion.





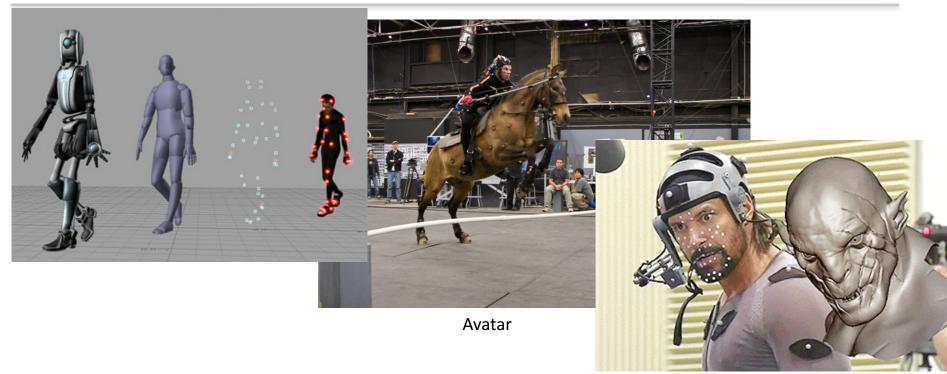
Early use of visual information to infer moving shape features



Etienne Jules Marey (1883): Chronophotographie géométrique, man locomotion.





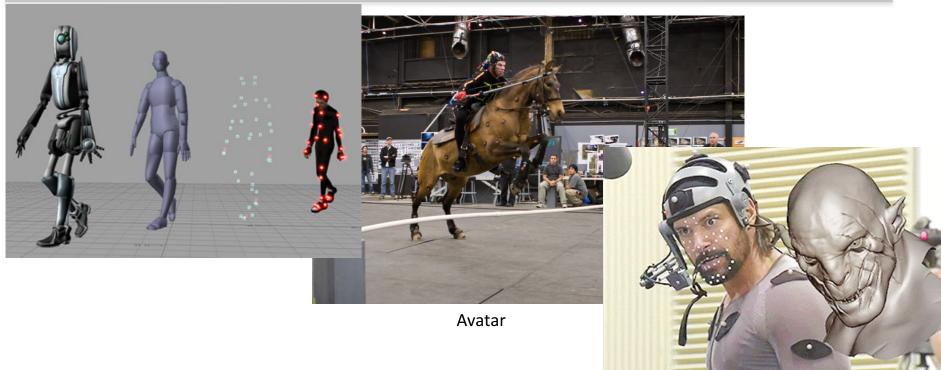


The Hobbit

Motion Capture systems using markers:







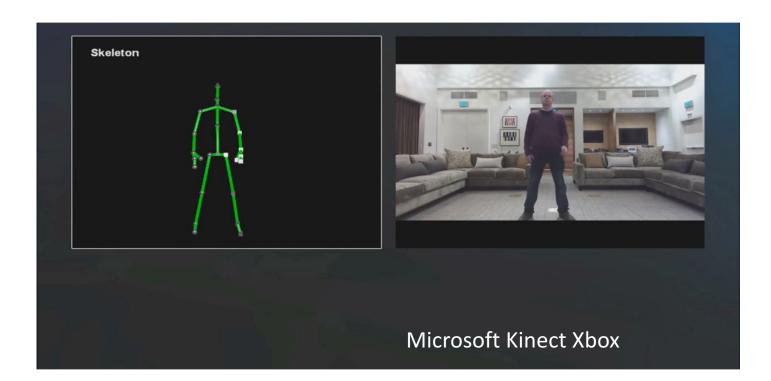
The Hobbit

Motion Capture systems using markers:

- Markers provide sparse motion information;
- No information on shapes or their appearances.







- Observations: depth fields;
- Outputs: skeleton poses, orientations, etc.







Instead of sparse marker locations or depth fields, multi-view systems can consider full color image information to produce 4D models.









4D Modeling Applications:

- Media contents.
- Motion Analysis:
 - Sport analysis;
 - Diagnostics in medical applications.
- Interactive and Immersive environments:
 - Gesture interfaces;
 - Games.



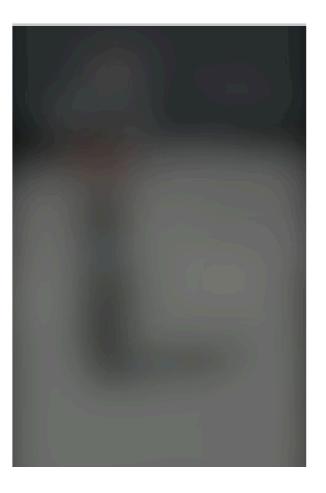




4D Modeling Applications: Media content production (4D View Solutions - startup INRIA)









4D Modeling Applications: VR and AR contents (Holooh@Paris)







Submission Id: 0063

VIRTUALIZATION GATE

INRIA / Grenoble Universities 4D View Solutions

[INRIA DEMO SIGGRAPH 2009]

4D Modeling Applications: Interactive and Immersive environments.





Some 4D modeling research issues:

- Modeling both shapes and appearances of complex scenes:
 - Acquisition issues: camera with different modalities, segmentation;
 - Shapes and appearances: learning over time;
- Recovering robust motion information.
- Modeling and analyzing motions/gaits.
- Animation Synthesis.





Outline

- 1. Multi-View platforms.
- 2. Shape recovery: basics.
- 3. Motion recovery: shape tracking.





Outline

1. Multi-View platforms.

- 2. Shape recovery: basics.
- 3. Motion recovery: shape tracking.







MPI Tubingen 4D Scanner [Siggraph'15]: Active system

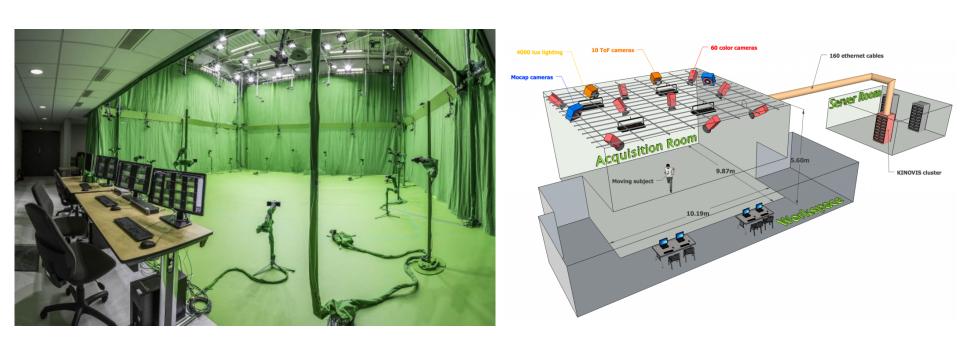




Dyna: A Model of Dynamic Hum	an Shape in Motion (SIGGRAPH 2015)	© <
	4D Scanner	
• • • • • • • • • • • • • • • • • • •		🖿 🔅 You 🖽 🕄 🕇





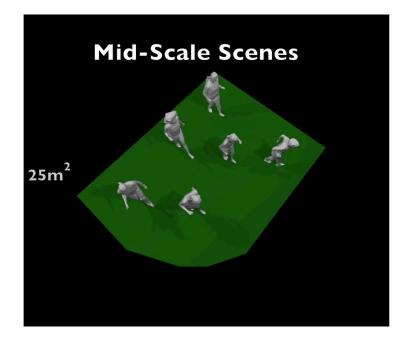


Kinovis platform at INRIA Grenoble









Kinovis platform@inria (64 cameras)







@Microsoft, High-Quality Streamable Free-Viewpoint Video, Siggraph'15 Combined passive and active system







@Microsoft, High-Quality Streamable Free-Viewpoint Video, Siggraph'15





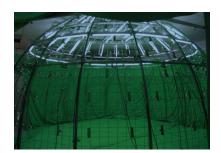


University of Surrey





University of Kyoto





University of Tsinghua

Model free shape estimation







MPI Sarrebrucken

Model based shape estimation



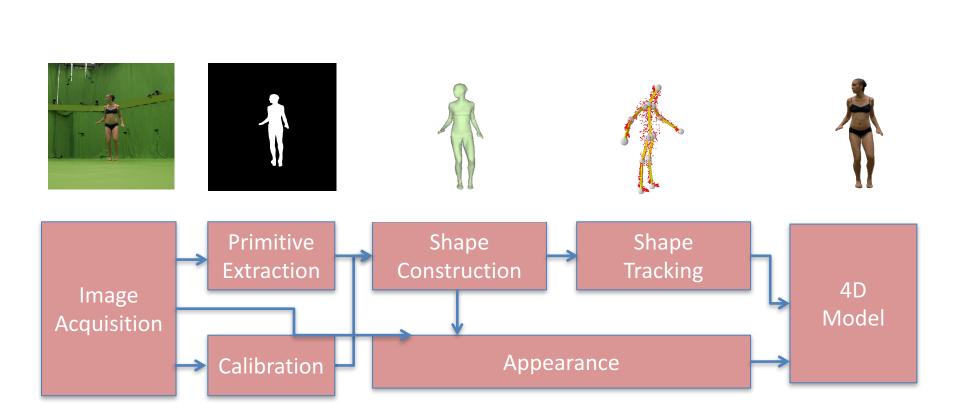


Outline

- 1. Multi-View platforms.
- 2. Shape recovery: basics.
- 3. Motion recovery: shape tracking.



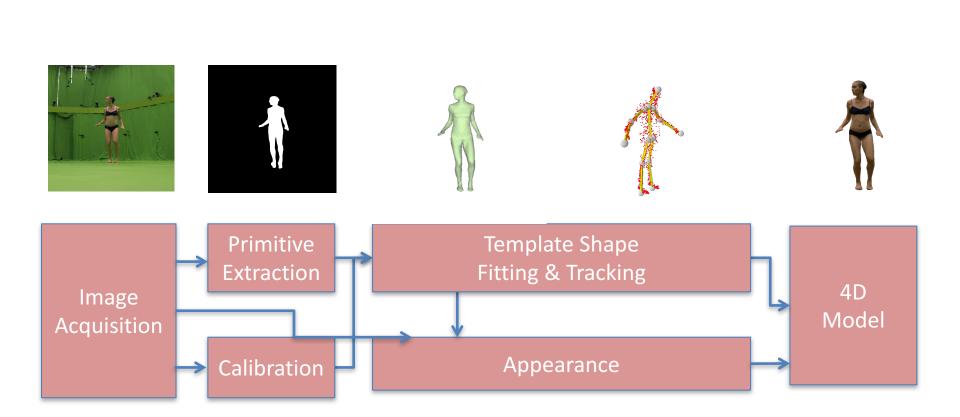




General 4D modeling pipeline: no prior model







General 4D modeling pipeline: prior model





Primitive Extraction

- Regions (silhouettes) -> surfaces, volumes
- Points (image features) -> 3D point clouds





Primitive Extraction

- Regions (silhouettes) -> surfaces, volumes
- Points (image features) -> 3D point clouds





Silhouette





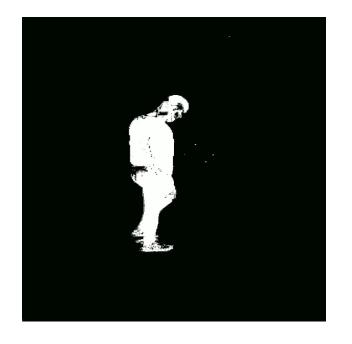
- Silhouettes are regions in the images where object of interest project.
- Silhouettes are estimated using low-level processes.
- Silhouettes give information on the observed surfaces.
- Extraction:
 - Chroma keying (blue or green background != skin color)
 - Background subtraction (static background)





Silhouette Segmentation

- Background subtraction:
 - Statistical background model
 - Gaussian
 - Gausian mixtures
 - Non parametric: e.g. histograms.
 - Issues:
 - Image digitalization (noise);
 - Color ambiguities between background and foregroud objects;
 - Luminosities changes, etc.





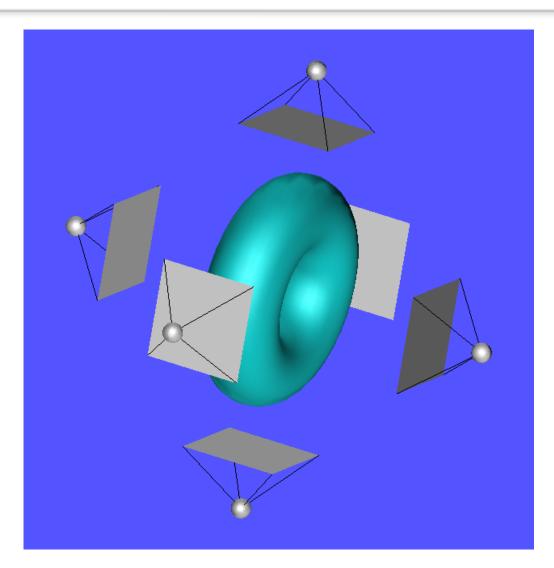


From silhouettes to shapes:

2D silhouettes define a volume in 3D called the visual hull. It is the maximal volume compatible with a set of silhouettes.

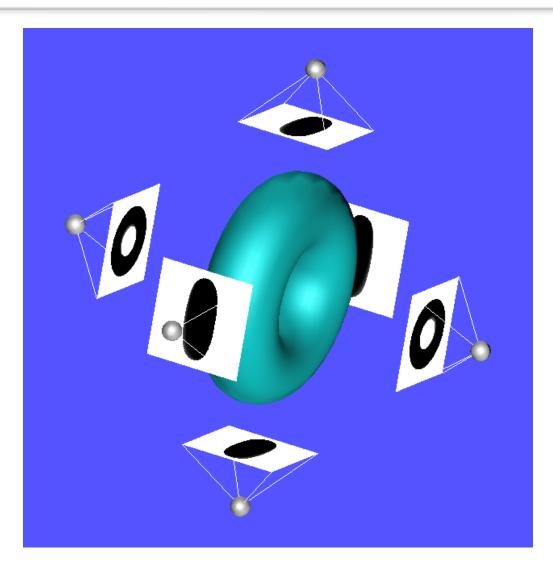






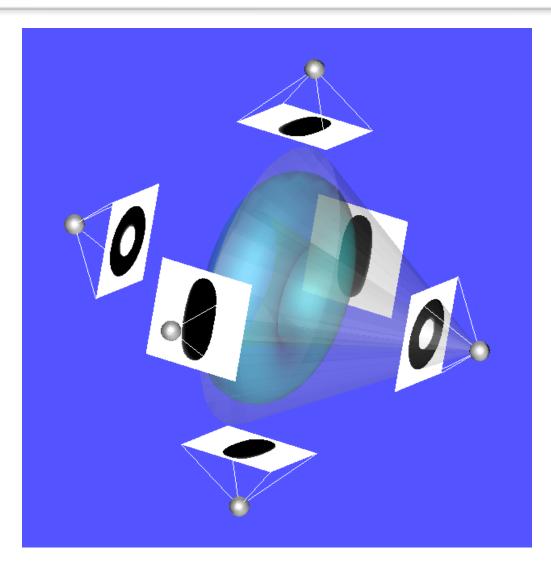






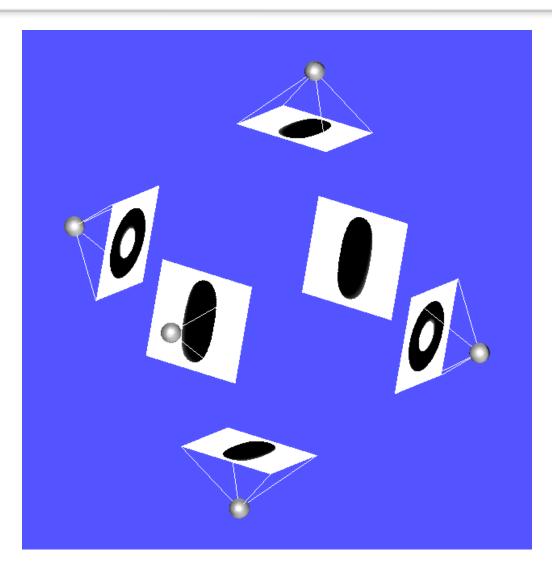






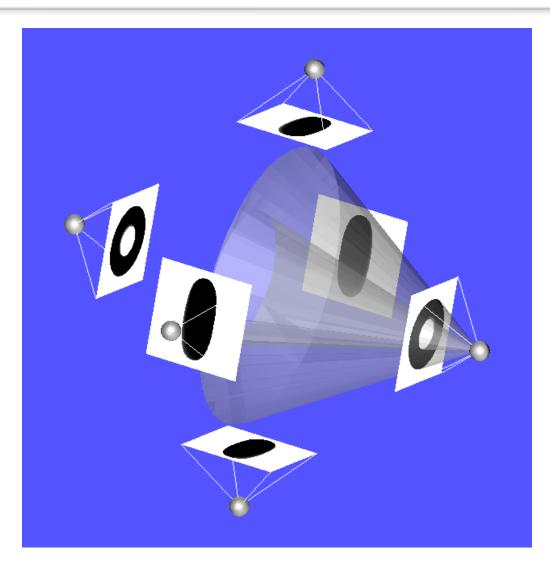






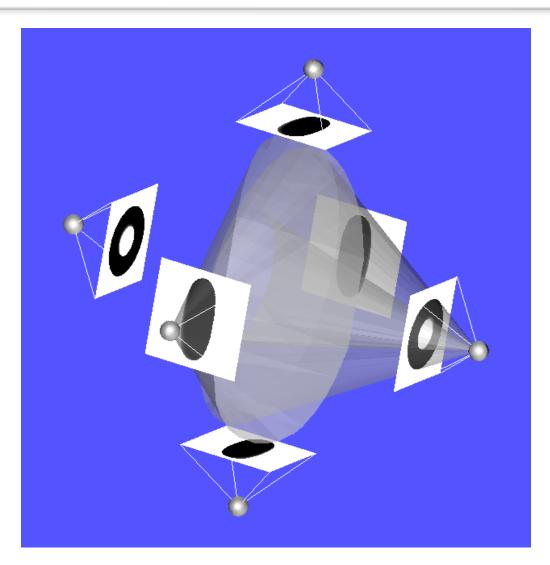






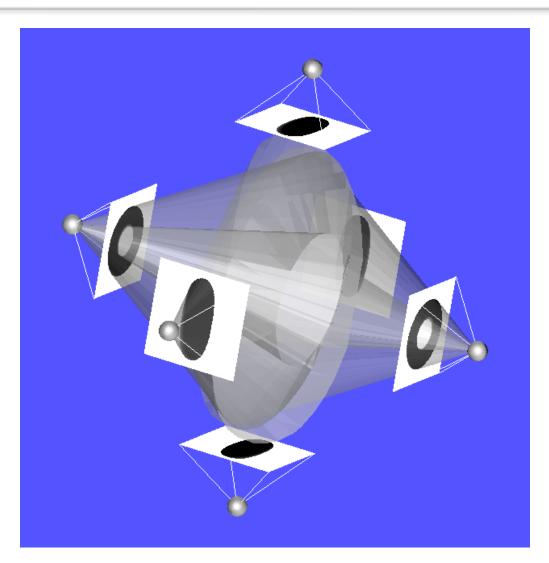






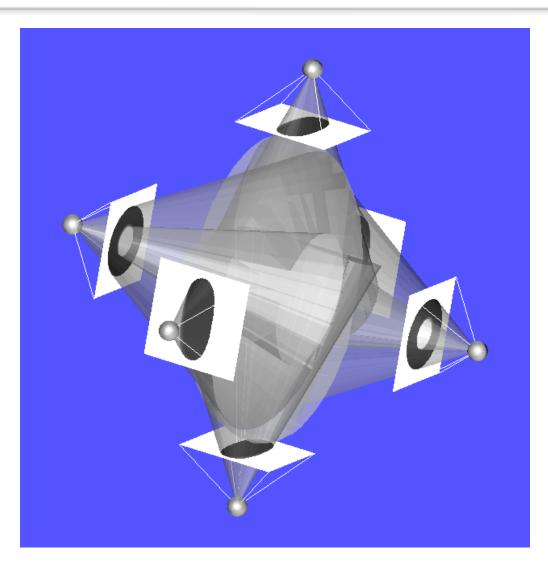






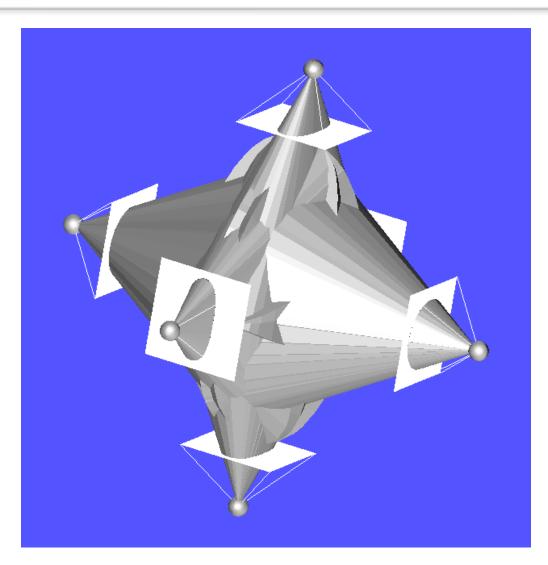






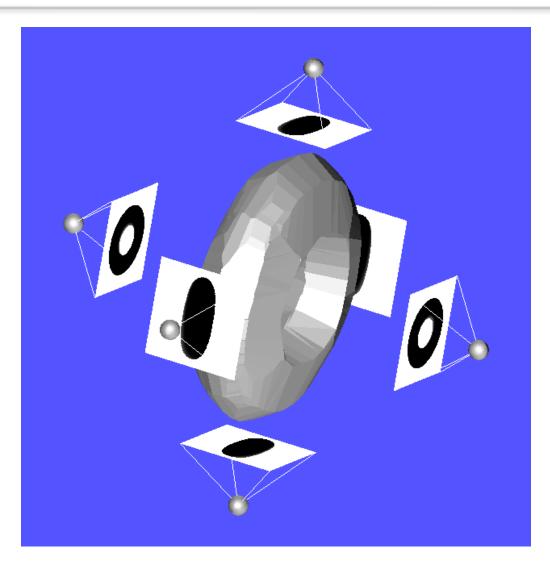






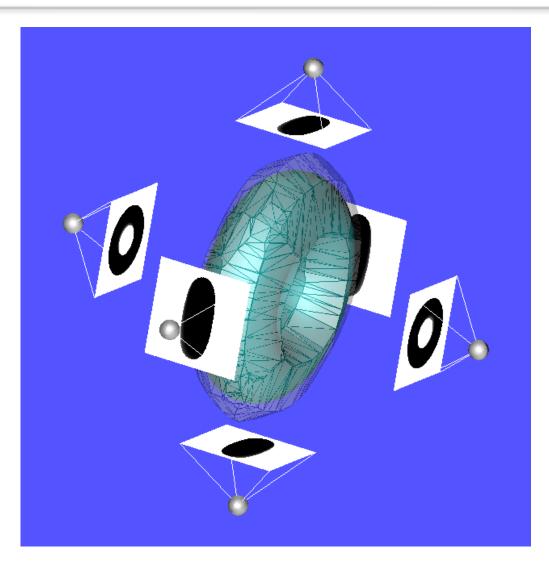








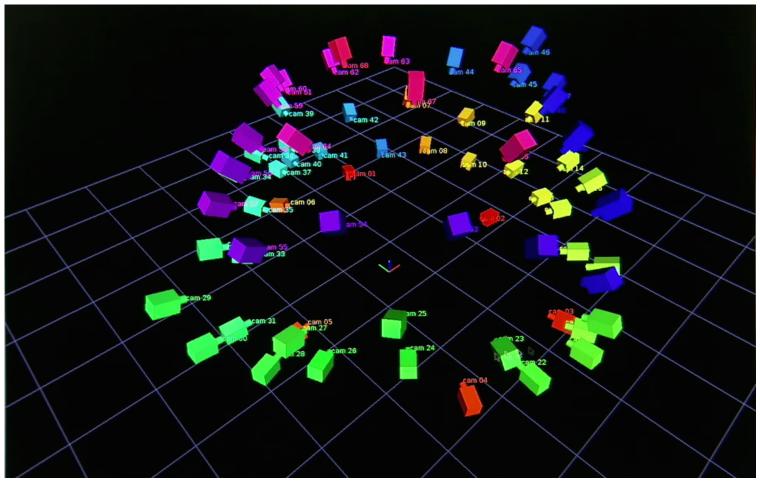








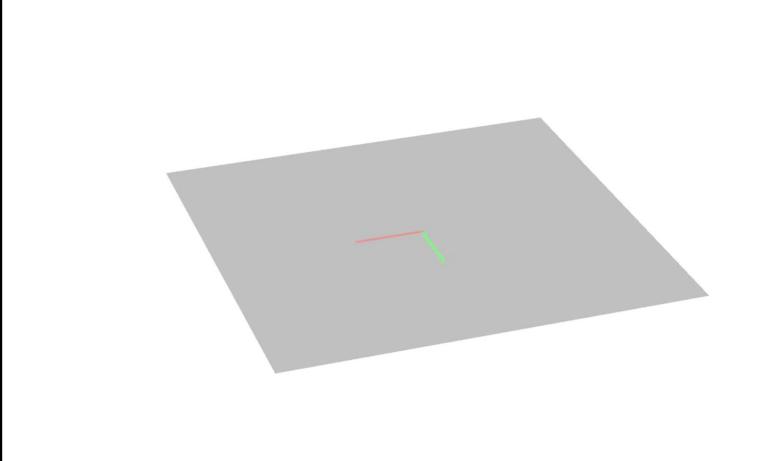
Real time Visual hulls with 67 cameras







Real time Visual hulls with 67 cameras







Primitive Extraction

- Regions (silhouettes) -> surfaces, volumes
- Points (image features) -> 3D point clouds





Getting 3D points

- Depth cameras (active system)
- Multi-view stereo with color cameras (passive system)





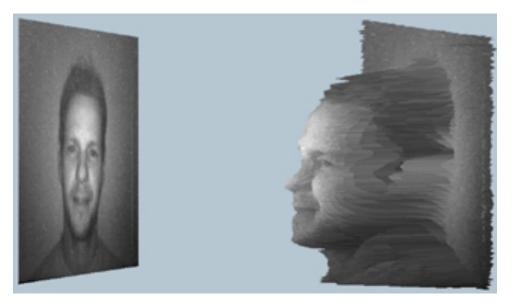
Getting 3D points

- Depth cameras (active system)
- Multi-view stereo with color cameras (passive system)
- Some platforms (e.g. Microsoft) are using both.
- While directly providing 3D information, active system have inherently more limitations than passive ones (e.g. scale, illumination).





Depth cameras

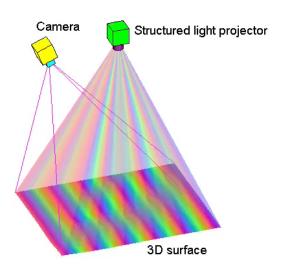


Time of flight cameras





Depth cameras

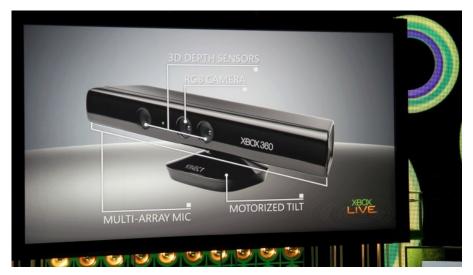


Structured light systems

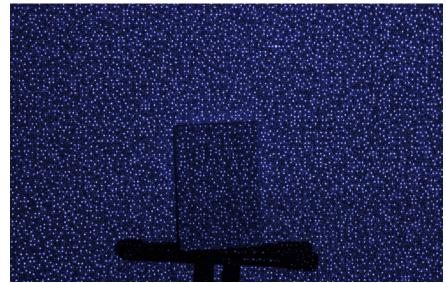




Depth cameras



Microsoft Kinect 1 (Primesense)

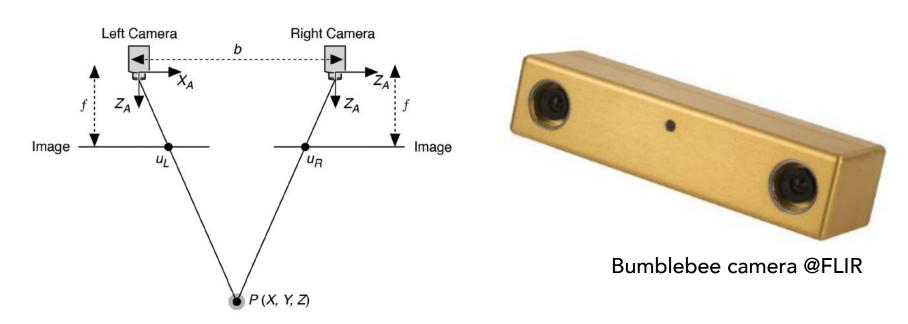


Infrared pseudorandom pattern (©PrimeSense) with a book in front.





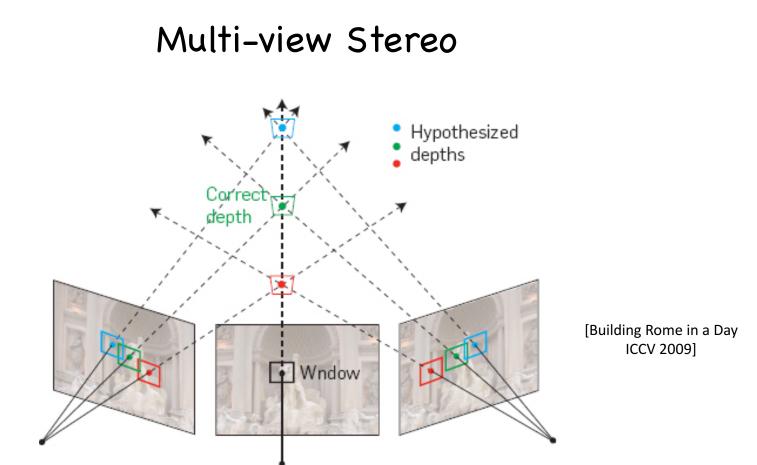
Depth cameras



Stereovision cameras: point must be matched in the 2 images







As with the stereo, image points are matched but more than 2 images are considered.





Multi-view Stereo

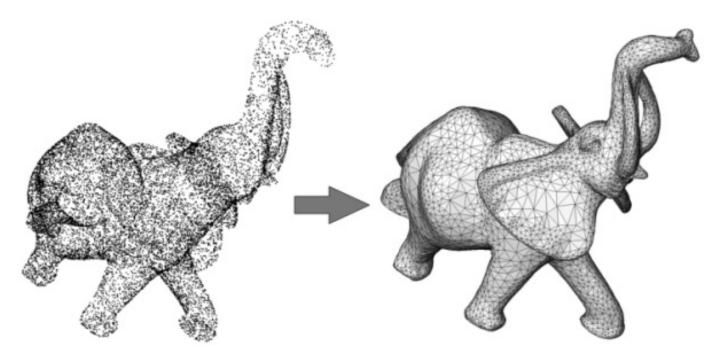


Building Rome in a Day, ICCV 2009 Agarwal, Furukawa, Snavely, Simon, Curless, Seitz, Szeliski.





From 3D points to Shapes

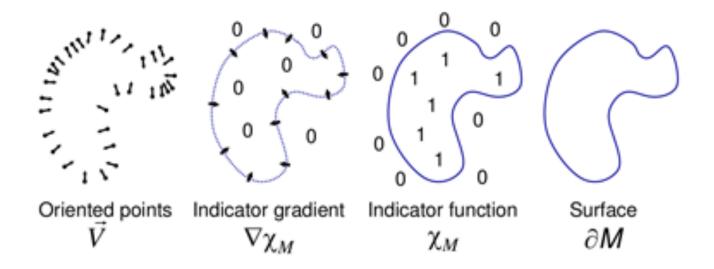


Example with: Poisson Surface Reconstruction, SGP 2006 M. Kazhdan, M Bolitho & H Hoppe





From 3D points to Shapes

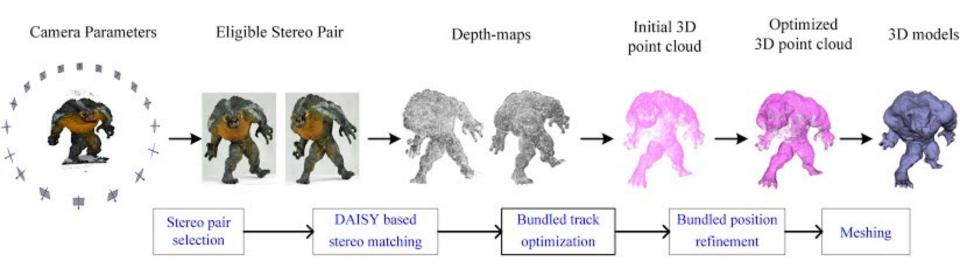


Poisson Surface Reconstruction, SGP 2006 M. Kazhdan, M Bolitho & H Hoppe





Points / Features



@ Jianguo Li, Eric Li, Yurong Chen, Lin Xu, Intel Labs China



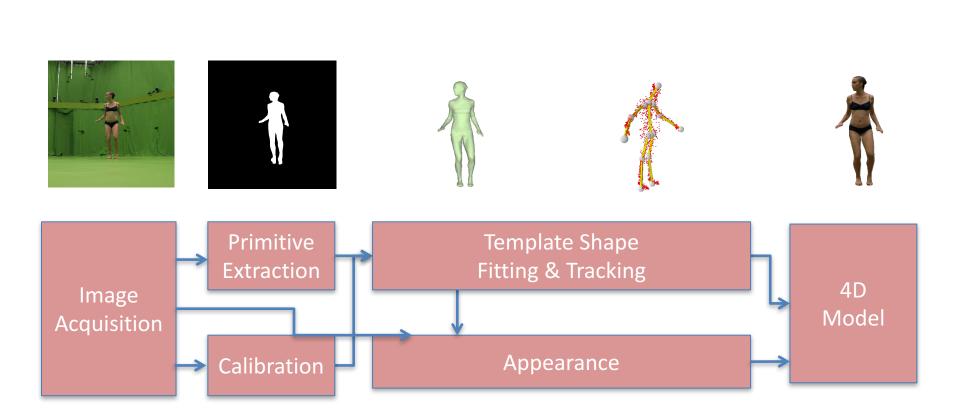




@Microsoft, High-Quality Streamable Free-Viewpoint Video, Siggraph'15







General 4D modeling pipeline: prior model





Dyna: A Model of Dynamic Hum	4D Scanner	
0:50 / 7:07		You Tube 📫 🕻





Prior Models: Shape Spaces



[Caesar human dataset, Siggraph 2003, Allen, Curless, Popovic]

PCA strategy allows to represent shapes with « eigen » shapes





Appearance



INRIA Kinovis







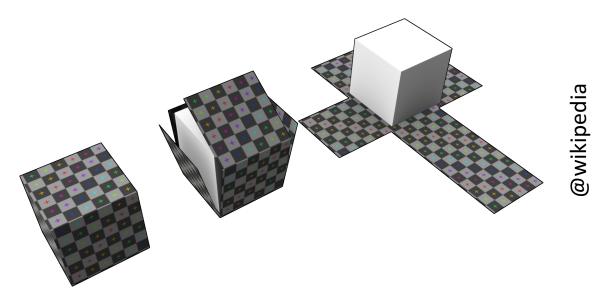






Appearance

1. At each frame, unwrap the mesh to define a 2D atlas where appearance (texels) can be specified.



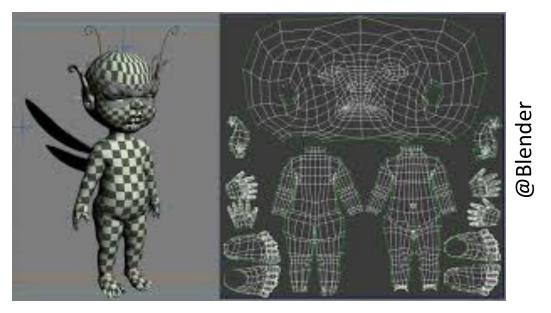
1. Map the observed images at the given frame onto the UV atlas to define a 2D texture map at each frame.





Appearance

1. At each frame, unwrap the mesh to define a 2D atlas where appearance (texels) can be specified.



1. Map the observed images at the given frame onto the UV atlas to define a 2D texture map at each frame.





Appearance





Some challenges

• Visual redundancy • Camera inaccuracies



 Noisy input images



over space



 Reconstruction inaccuracies





Occlusions

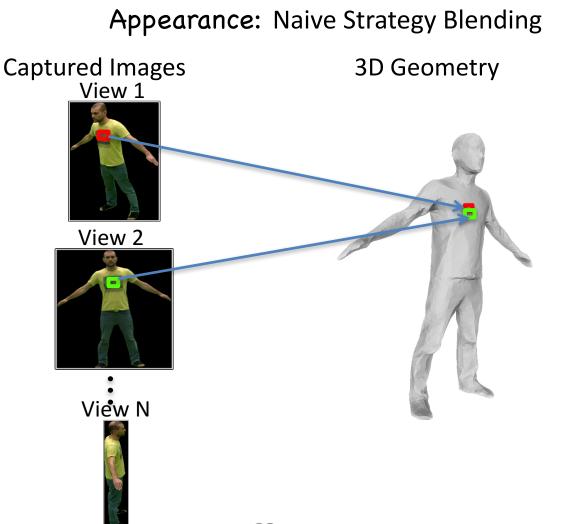


• Visual redundancy over time



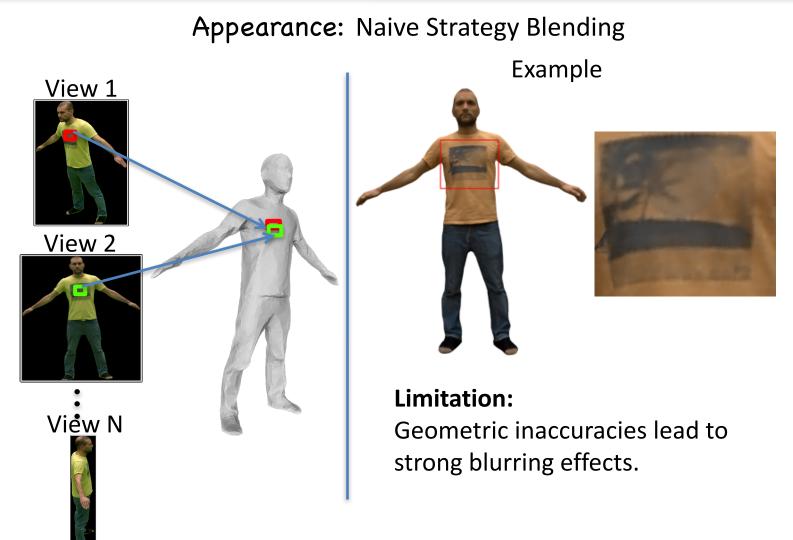






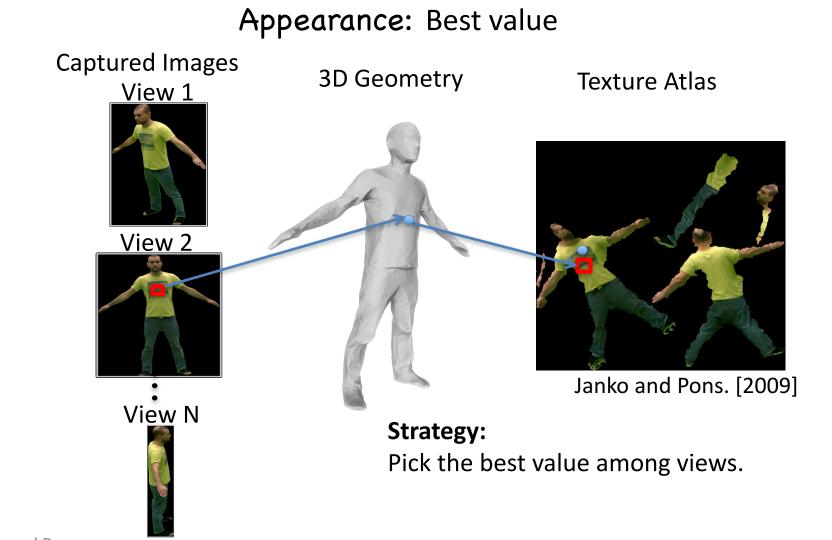






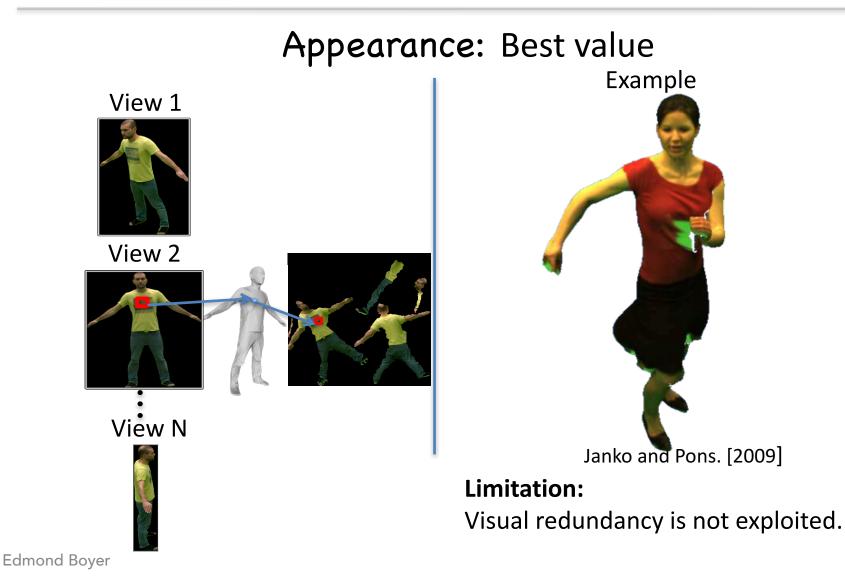








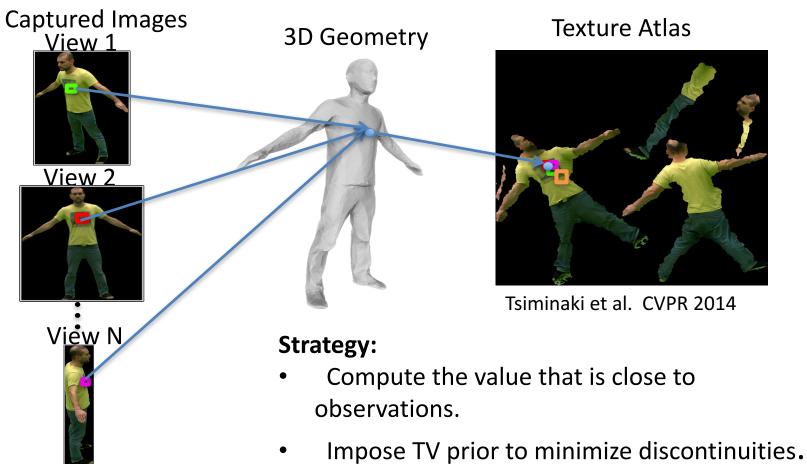








Appearance: Super Resolution Strategy

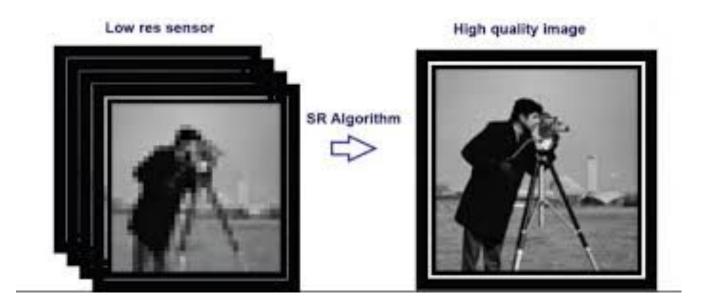






Shape Recovery: Basics

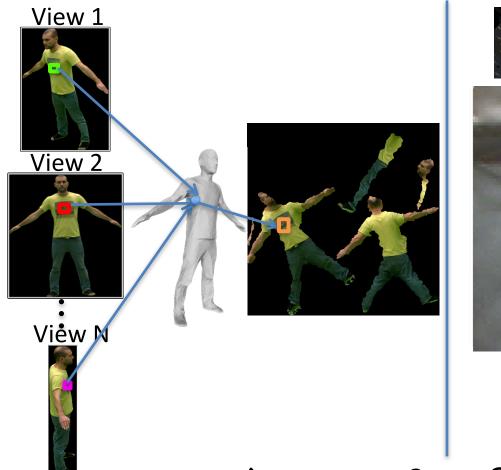
Image Super-resolution







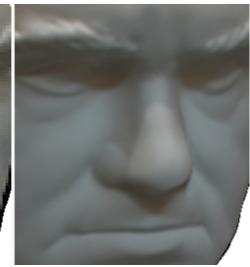




Example: Input Images







Input

Tsiminaki et al. CVPR 2014

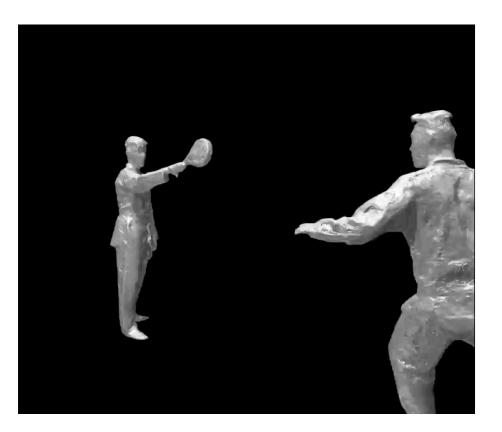
Appearance: Super Resolution Strategy





Shape Recovery: Basics









Outline

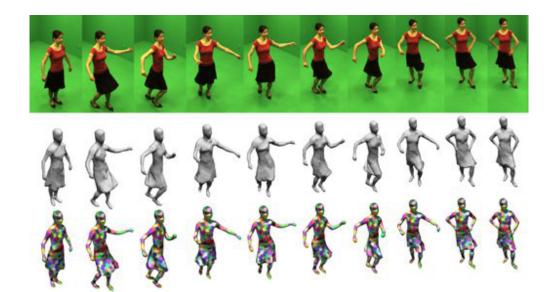
- 1. Multi-View platforms.
- 2. Shape recovery: basics.
- 3. Motion recovery: shape tracking.





Motion Recovery

- Problem: Given visual data (images, 3D shapes, etc.) and a motion model (parametric, non-parametric) recover motion parameters, e.g. the joint angles in the case of a skeleton model.
- Motivation: Motion is an important information to model shape evolutions
- Remark: In many vision applications this consists in recovering the pose of a given model (e.g. skeleton, shape) at each time instant over a sequence.







Motion Recovery

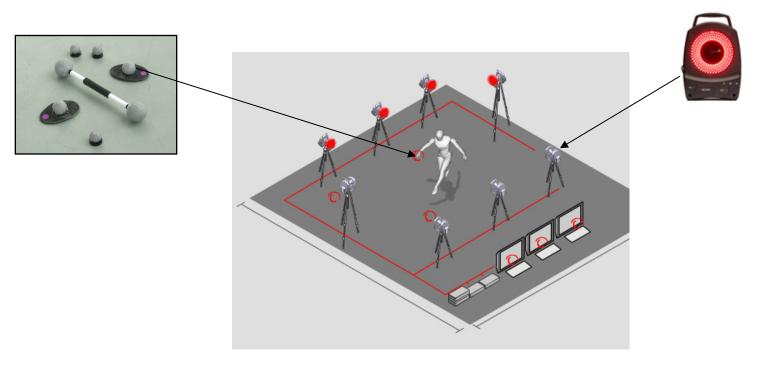
- Optical methods with markers:
 - Observations: markers are tracked in calibrated images
 - Passive markers: retroreflective markers
 - Active markers: markers emit their own lights for identification (e.g. different pulses per markers).
 - Motion recovery: a motion model (e.g. a skeleton) is matched with the marker locations.
 - Applications: "Motion capture" of bodies (with articuled models), faces (with deformable meshes), etc.
- Non optical methods with markers also exist: inertial or magnetic systems for instance.





Motion Recovery

- Marker based approaches, e.g. the Vicon system:
 - High precision cameras (up to 16 Mpixels) and high frequencies (> 400Hz).







Motion Modeling

Markerless approaches:

- Observations: 2D (contours, silhouettes), 3D (points, shapes) in a single or multiple calibrated images.
- Motion recovery: the model is matched to the observations:

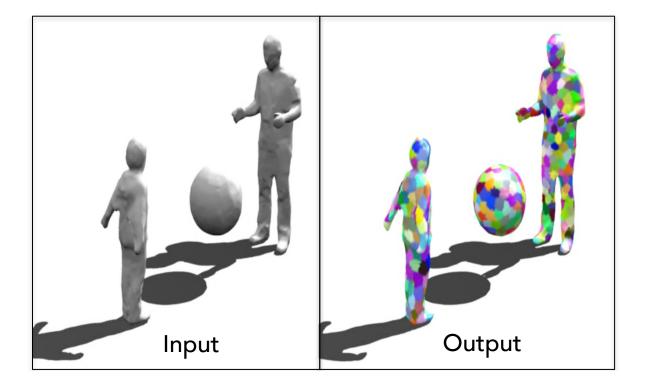
 Parametric motion models: find the best model parameters (e.g. joint angles) such that the model explains the observations.
-> Shape Tracking

• Non parametric models: find the best model (in a database) that explains the observations.





Given 2D/3D observations at different instants recover time consistent shape models (4D models).







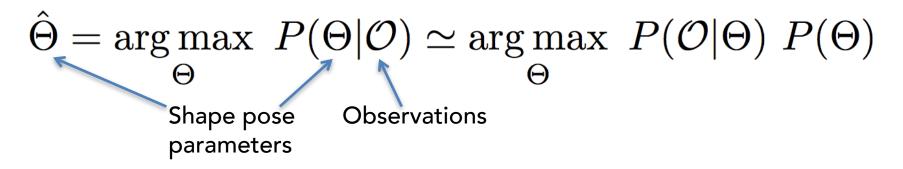
Problem Formulation: MAP estimation

$\hat{\Theta} = \underset{\Theta}{\arg \max} P(\Theta|\mathcal{O}) \simeq \underset{\Theta}{\arg \max} P(\mathcal{O}|\Theta) P(\Theta)$





Problem Formulation: MAP estimation



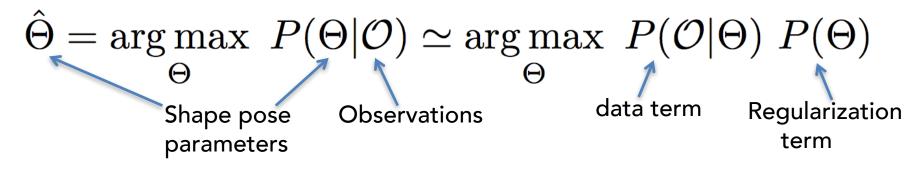
Shape pose parameters (motion parameterization): mesh vertices, locally rigid displacements, joint angles, learned,...

Observations: Meshes, 3D points, 2D silhouettes,..





Problem Formulation: MAP estimation



Shape pose parameters (motion parameterization): mesh vertices, locally rigid displacements, joint angles, learned,...

Observations: Meshes, 3D points, 2D silhouettes,..

Regularization (Prior): smooth trajectories, rigidity constraints,...



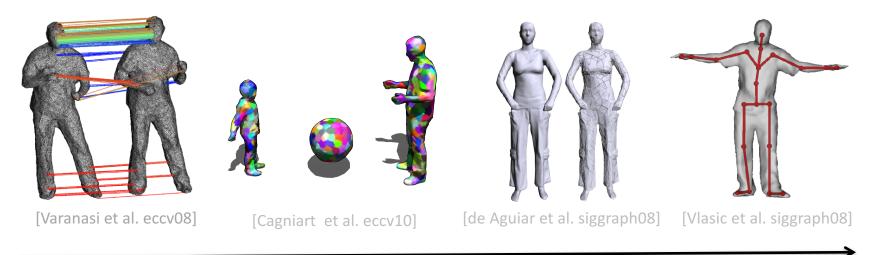


Constrained

Shape Tracking

Shape pose parameterization (**deformation model**):

Prior information that determines the classes of deformations.



Loose

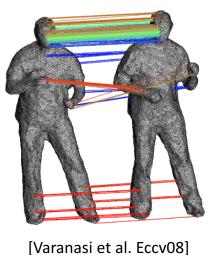




Model-free (motion fields)

• Scene flow: Pons et al., Neumann et al., Blache et al. etc.

• Feature based: Starck et al., Bronstein et al., Varanasi et al., etc.



Model-based

• Locally rigid: Gavrila et al., Kakadiaris et al., Cagniart et al. etc.

 Articulated: de Aguiar et al.,
Vlasic et al., Furukawa et al., Gall et al., etc

[Vlasic et al. SIGGRAPH08]





Model-free (motion fields)

• Scene flow: Pons et al., Neumann et al., Blache et al. etc.

• Feature based: Starck et al., Bronstein et al., Varanasi et al., etc.

- + Little prior knowledge
- Drift over time
- Outliers in feature matching

Model-based

• Locally rigid: Gavrila et al., Kakadiaris et al., Cagniart et al. etc.

 Articulated: de Aguiar et al.,
Vlasic et al., Furukawa et al., Gall et al., etc

[Vlasic et al. SIGGRAPH08]



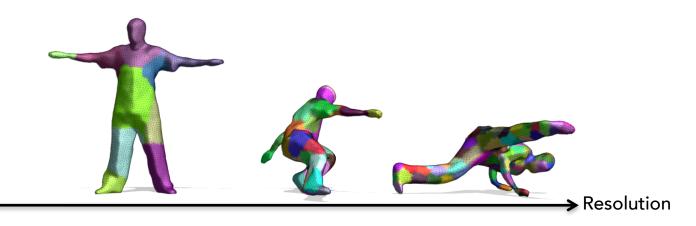


Model-free (motion fields)	Model-based
• Scene flow: Pons et al., Neumann et al., Blache et al. etc.	• Locally rigid: Gavrila et al., Kakadiaris et al., Cagniart et al. etc.
• Feature based: Starck et al., Bronstein et al., Varanasi et al., etc.	• Articulated: de Aguiar et al., Vlasic et al., Furukawa et al., Gall et al., etc
+ Little prior knowledge - Drift over time - Outliers in feature matching	+ Temporally consistent + Reduced drift - Limited class of motion/deformation





Patch based deformation model [Cagniart et al. eccv10]



A surface deformation model that is decoupled from the original geometry.

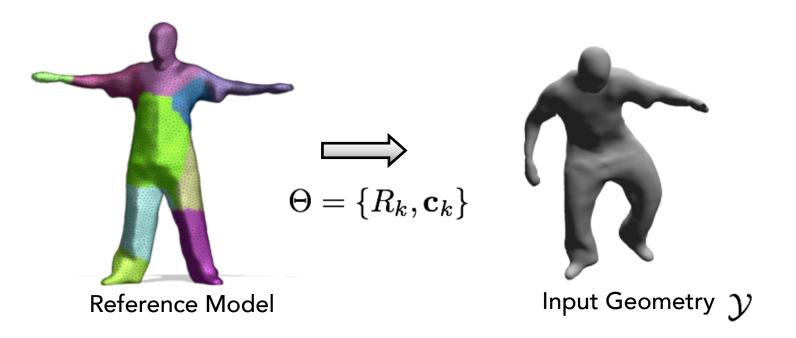
Deformation model:

- 1. Patches at different level of details are attached to the shape model.
- 2. Patches are assumed to move rigidly.





Shape pose parameterization







$\hat{\Theta} = \underset{\Theta}{\arg \max} P(\Theta|\mathcal{O}) \simeq \underset{\Theta}{\arg \max} P(\mathcal{O}|\Theta) P(\Theta)$

Data term: requires observation-model association

- Local deterministic approaches: closest points (e.g. ICP and most shape tracking methods);
- Local probabilistic approaches: soft associations with respect to distances (e.g. EM-ICP [cagniart 10], Coherent Point Drift [Myronenko & Song10]);
- Local but non-Sequential [Klaudiny et al. 12];
- Global approaches: global association (e.g. with optimal transport);
- Learned (e.g. Vitruvian manifold [Taylor et al. 12]) .



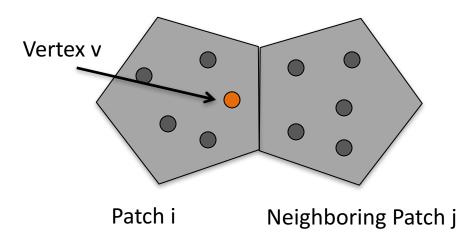


Regularization term:

- Motion field Smothness, e.g. Coherent Point Drift [Myronenko & Song10].
- Shape Preservation, e.g. laplacian coordinates [Sorkine et al.04] or local rigidity constraints [cagniart 10].
- Learned models, e.g. motion manifolds [Duveau et al. 12].

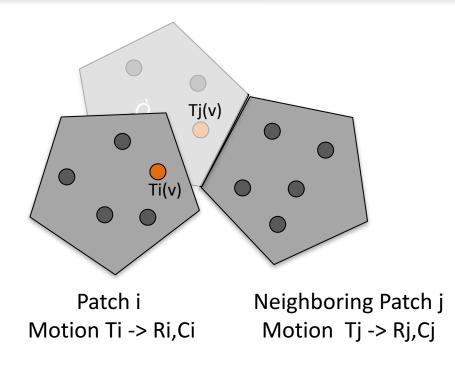






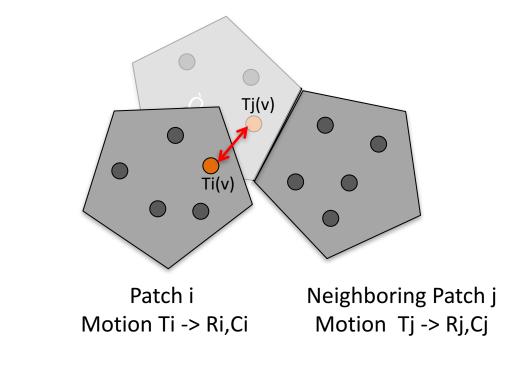












Associated (soft) rigidity constraints for vertex v:

Ti(v) = Tj(v) for all j in neighbors(i)





MULTI-OBJECT TRACKING : "BALLON" SEQUENCE

self occlusions, self intersections, outlying geometry

* data : INRIA PERCEPTION * 275 frames * input : photoconsistent meshes

Edmond Boyer





Shape Tracking: More



Combined simulated and captured Shape dynamics





Conclusion

Modeling evolving shapes:

- Pretty good models + deformations with simple scenes.
- Some results with the dynamic aspects: information redundancy, statistics for example.

Progress to be made:

- Acquisition: precision, robustness, modalities (X-ray).
- Shape: representation (e.g. clothes), changing appearances,
- Motion: build relevant models, pose spaces and motion spaces; statistical analysis.
- Datasets: benchmarks.

Fundamental issues:

- Shape models that account for material, appearance and anatomical information.
- Fully exploiting the time dimension to build models.
- Learning.





Website: <u>http://morpheo.inrialpes.fr</u>

Datasets: <u>http://4drepository.inrialpes.fr</u>