# MAP Visibility Estimation for Large-Scale Dynamic 3D Reconstruction

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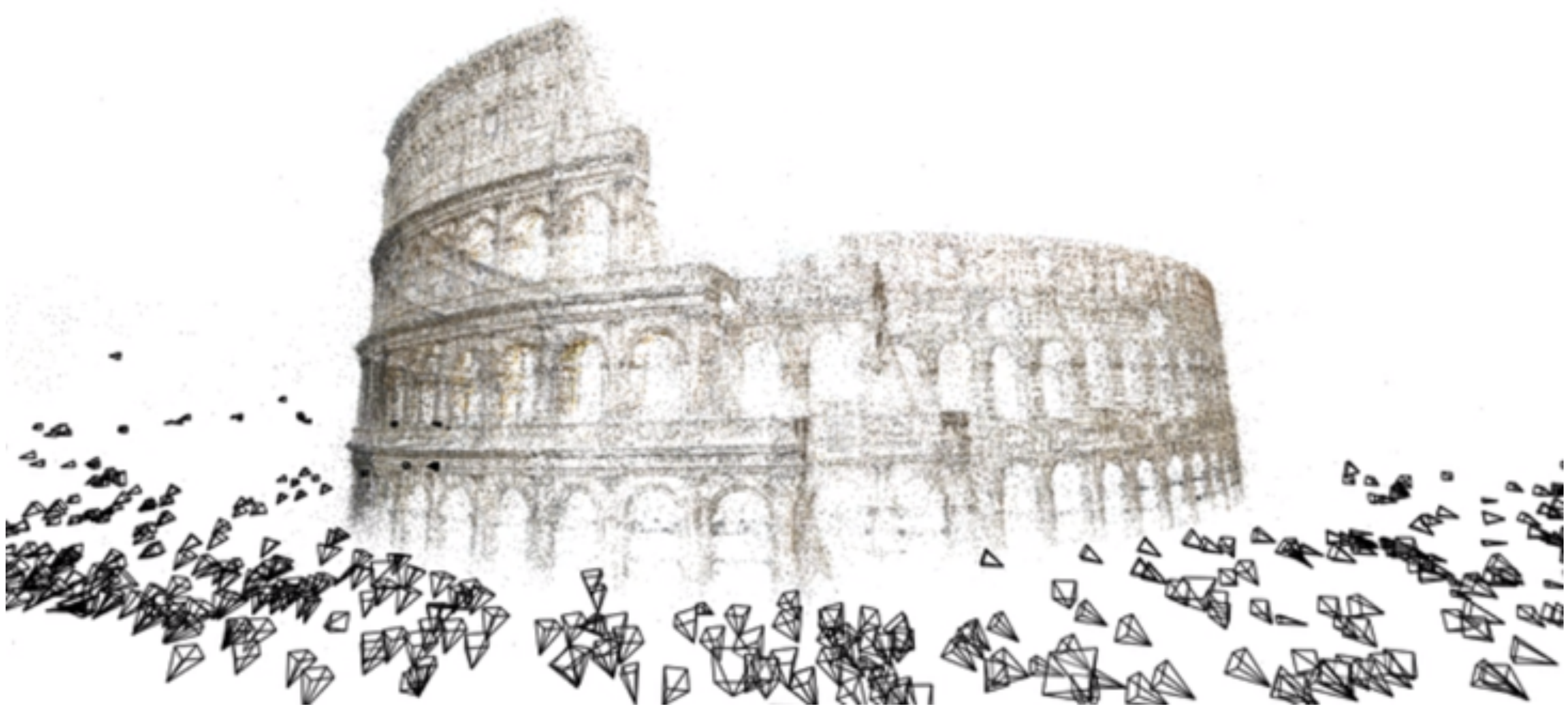
Carnegie Mellon University

# Large-scale 3D Reconstruction

## Utilizing a Large Number of Images



Dense

Accurate

Covering large area

[Snavely et al., SIGGRAPH 2006]
[Agarwal et al., ICCV 2009]

# Large-scale 3D **Event** Reconstruction

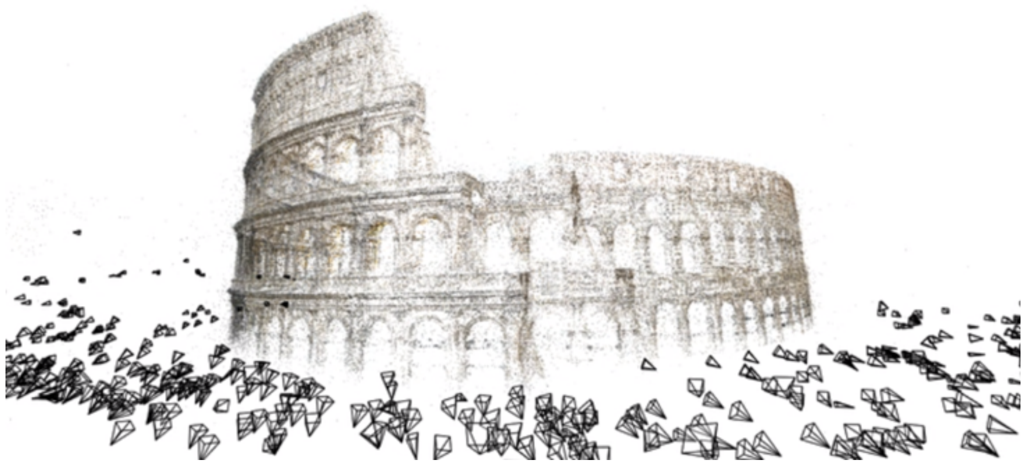
## New Opportunity from a Large Number of Videos

What can we reconstruct in dynamic scenes?

# Large-scale Dynamic **Event** Reconstruction

## What to reconstruct

**Static Scene**



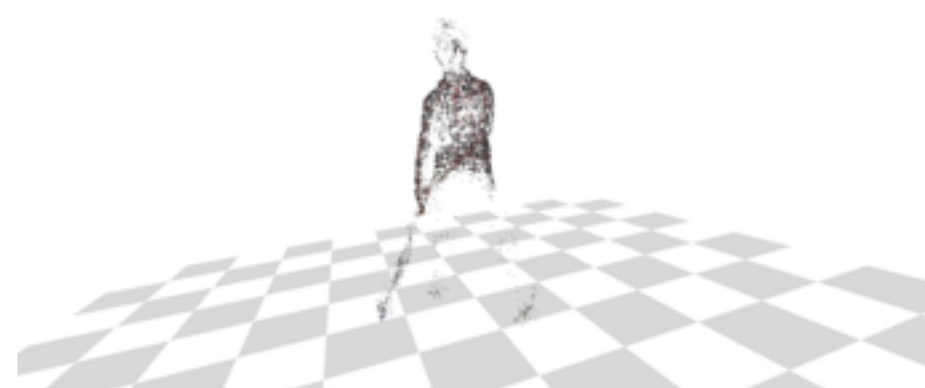
3D Point cloud
(3D shape)

Dense
Accurate
Covering Large area

**Dynamic Scene**

Dense
Accurate
Long-term

VS

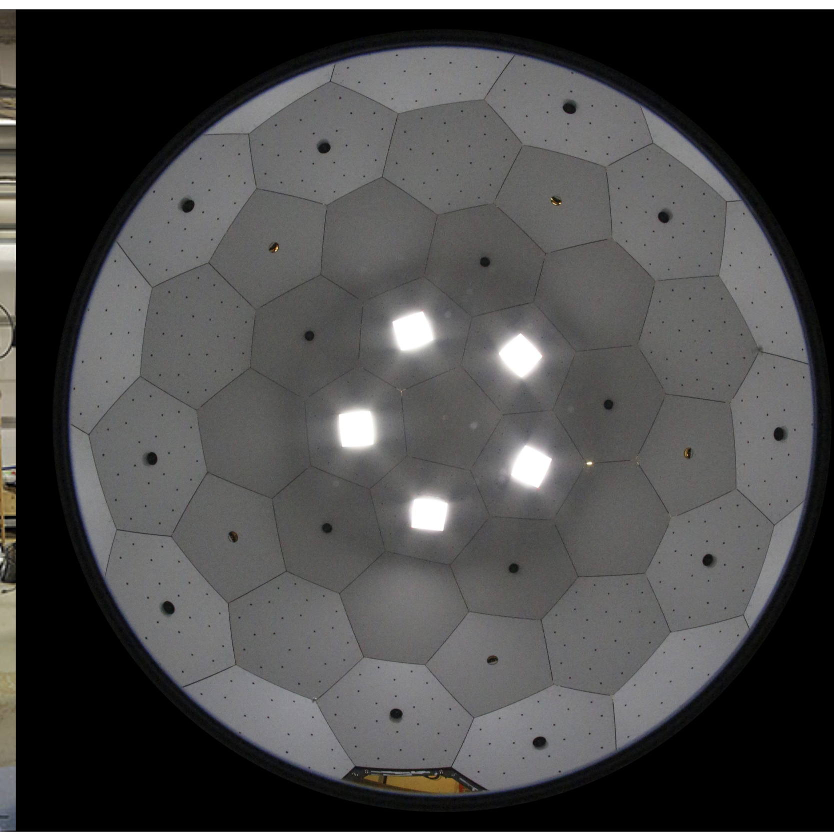


**Trajectory stream**
(3D shape + **3D motion**)

# CMU Panoptic Studio

## A System to Simulate Crowd Capture Videos

Geodesic Dome Exterior



Spherical Image (Interior)

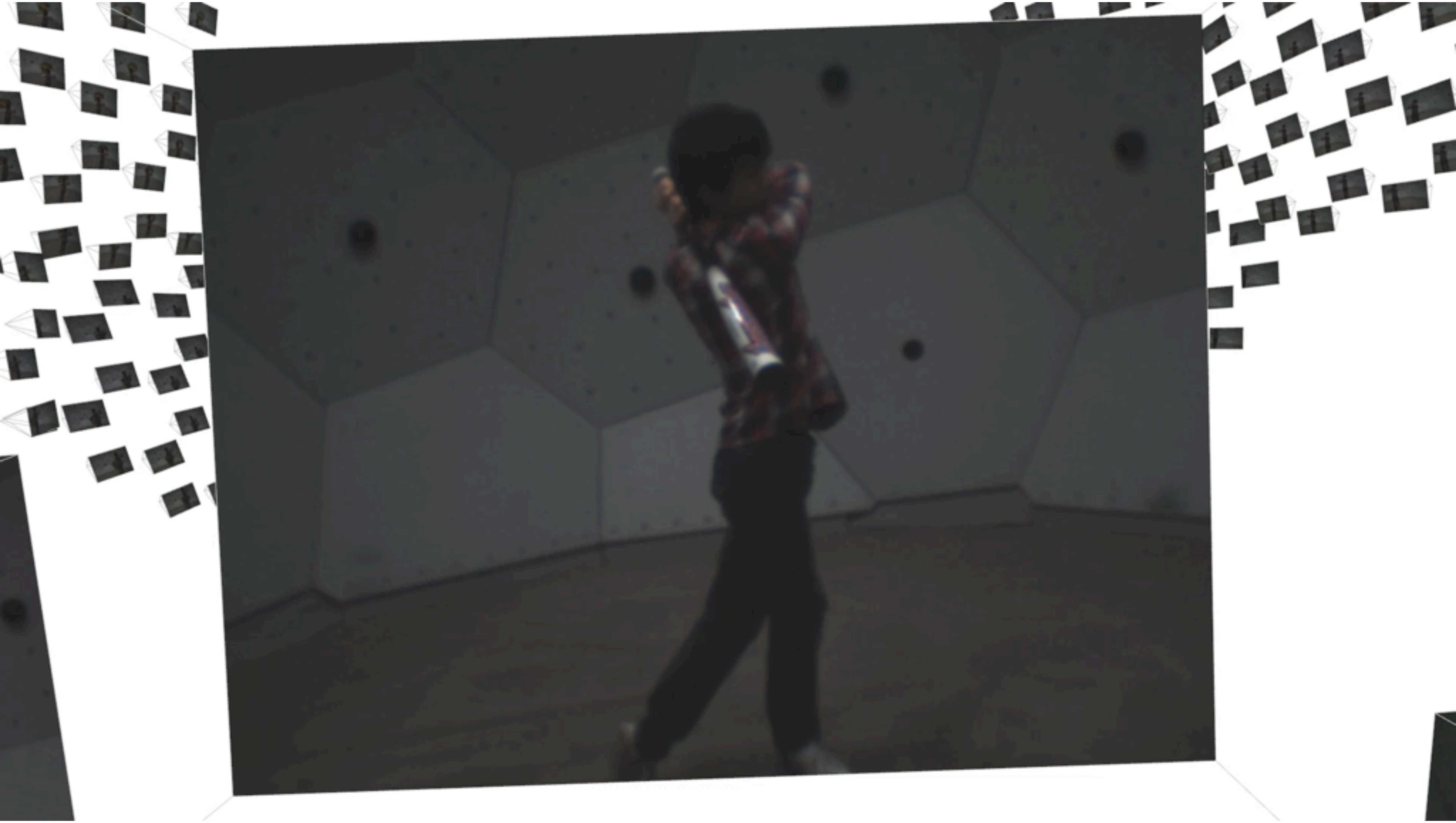
Looking in

# Input for Dynamic Event Reconstruction

## An Example View

# Input for Dynamic Event Reconstruction

480 Unique Viewpoints

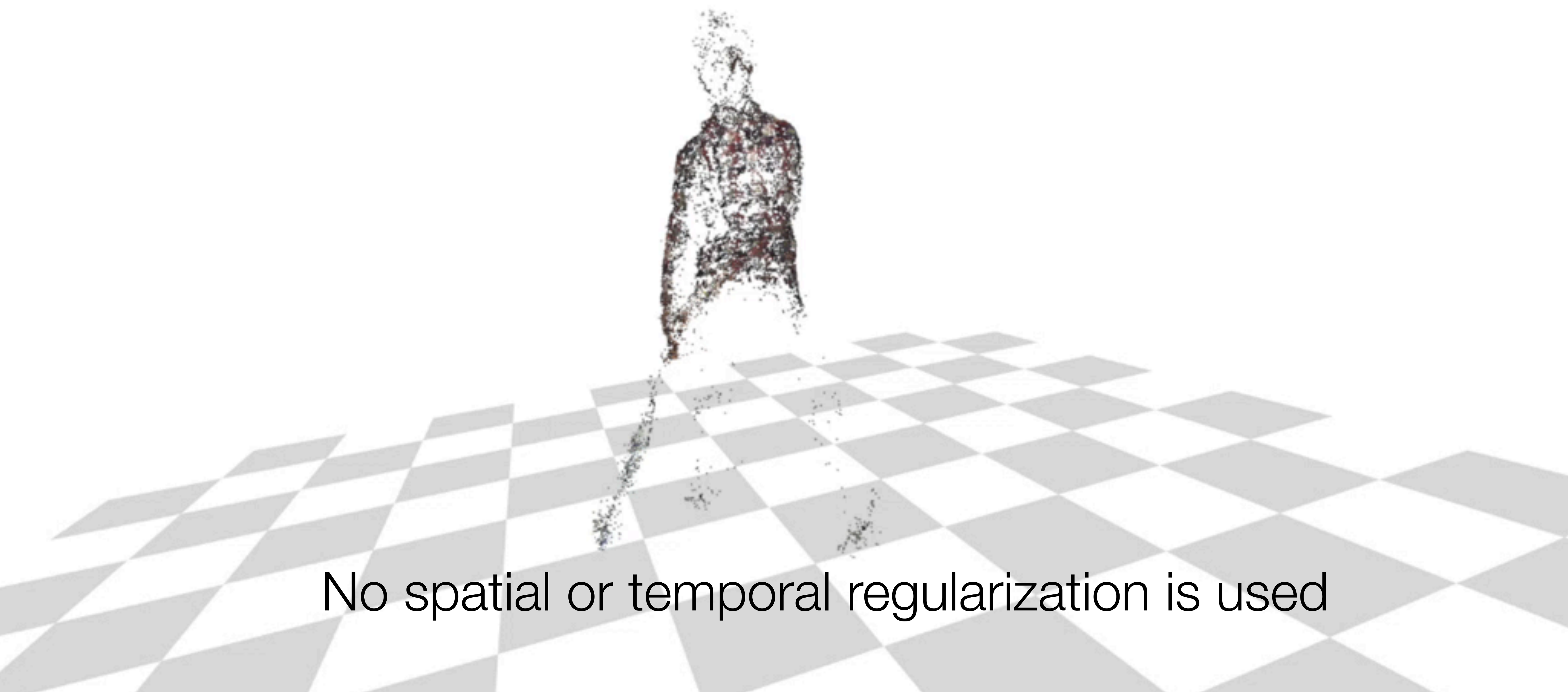


# Input for Dynamic Event Reconstruction

## All 480 Input Videos

# Large-scale Dynamic 3D Reconstruction

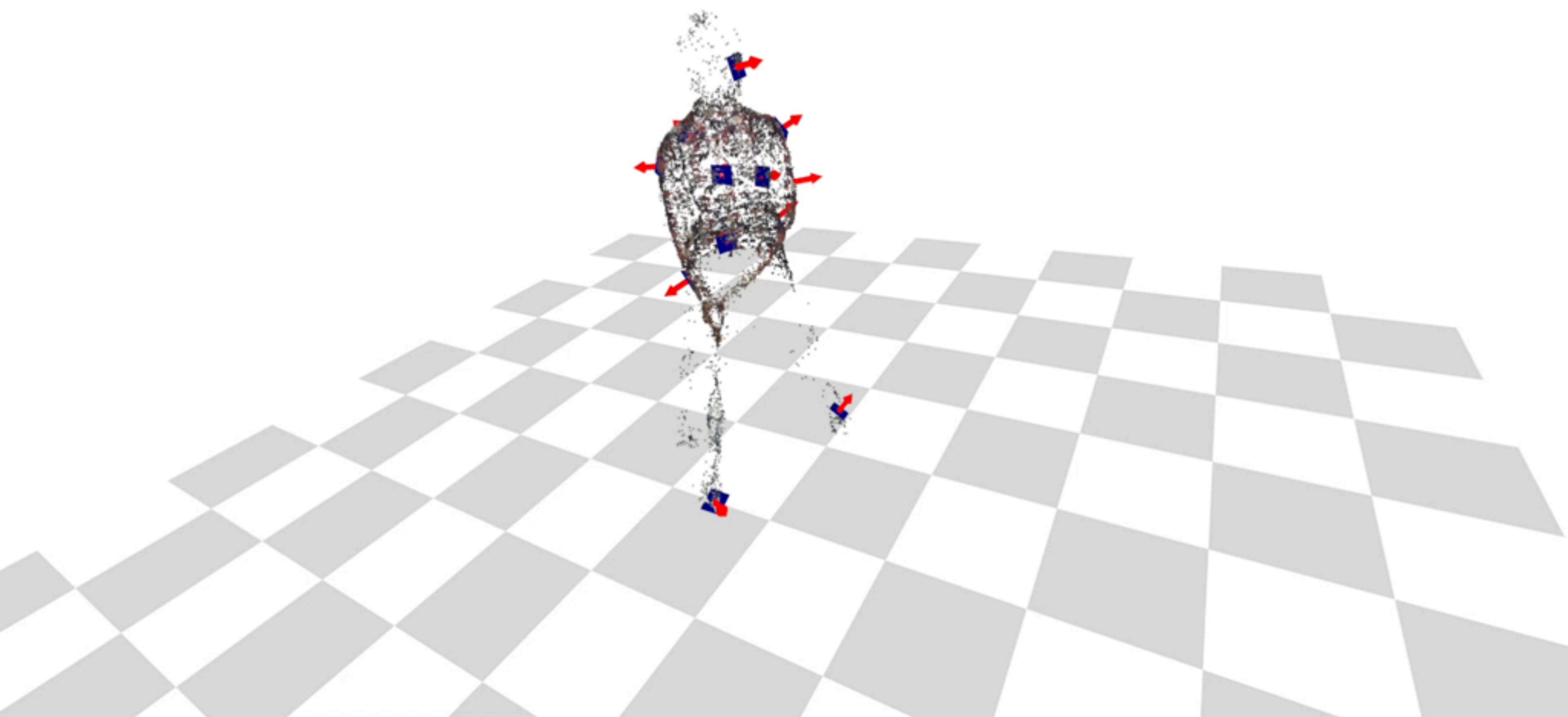
## 100,000 Trajectories over Hundreds of Frames



No spatial or temporal regularization is used

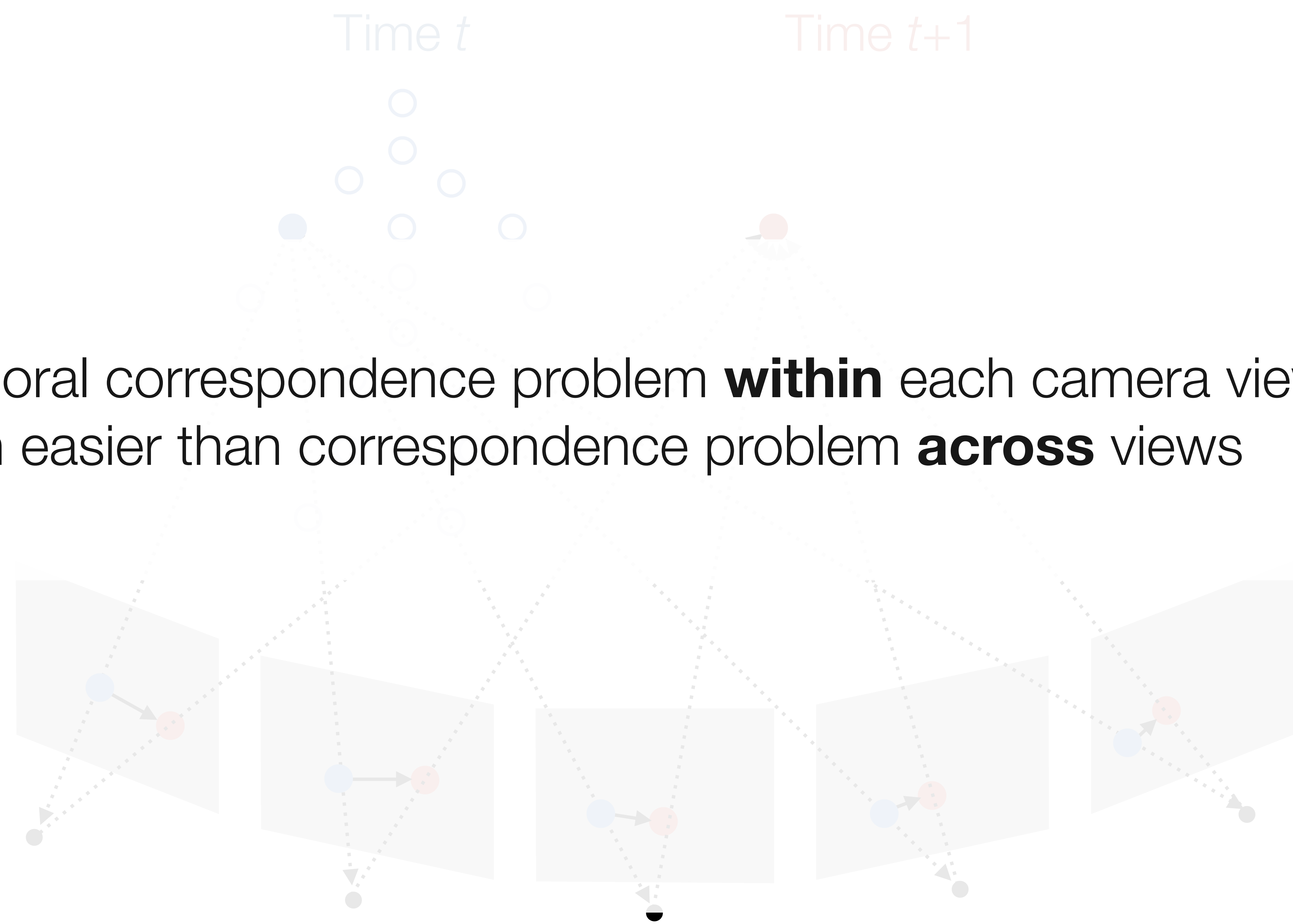
# Large-scale Dynamic 3D Reconstruction

## A Detailed View of Selected Patches



# Reconstructing 3D Trajectory

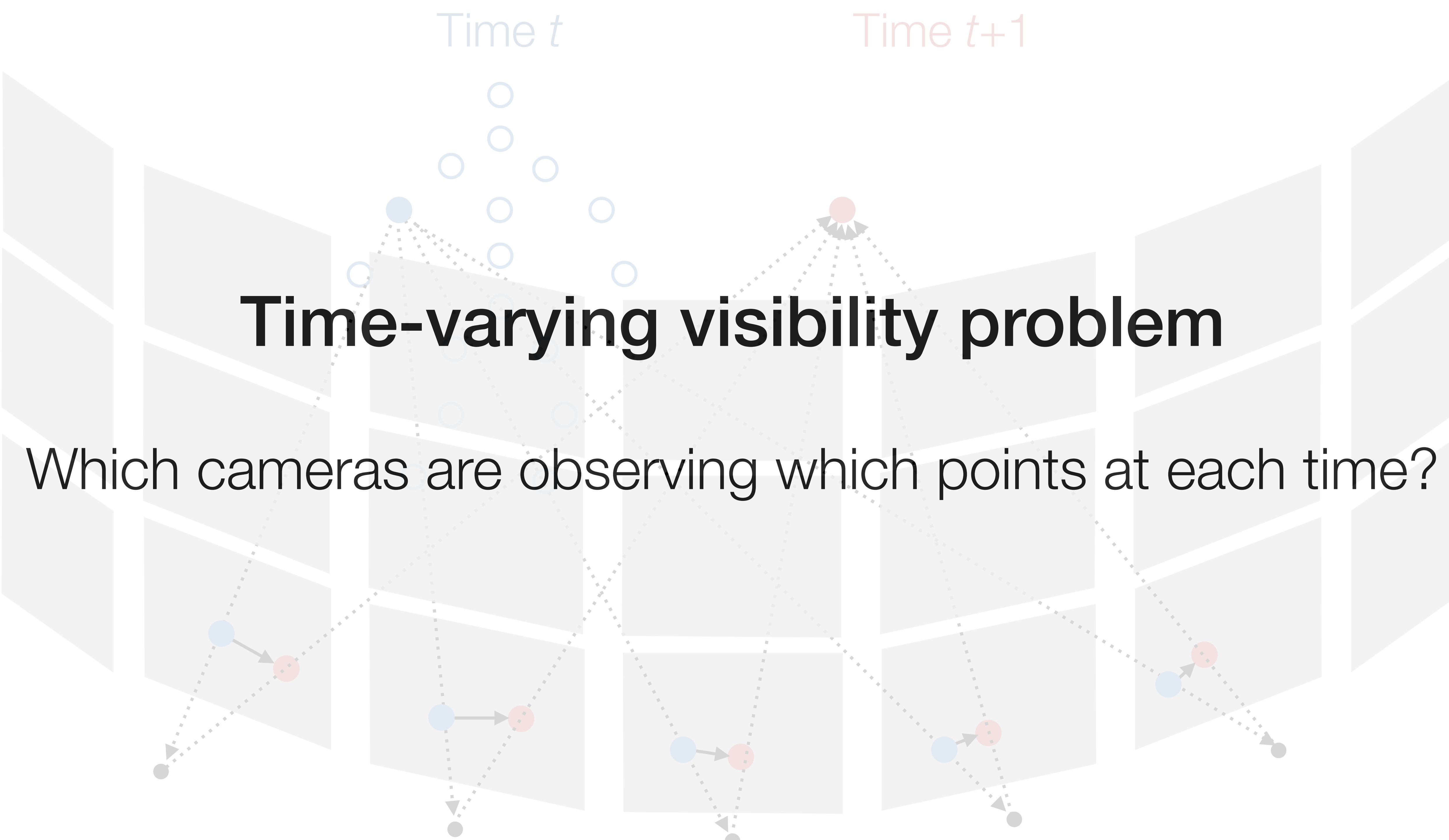
## 2D Flow-based Method




Temporal correspondence problem **within** each camera view is much easier than correspondence problem **across** views

# Reconstructing 3D Trajectory

## Key Issue To Leverage a Large Number of Views




**Time-varying visibility problem**

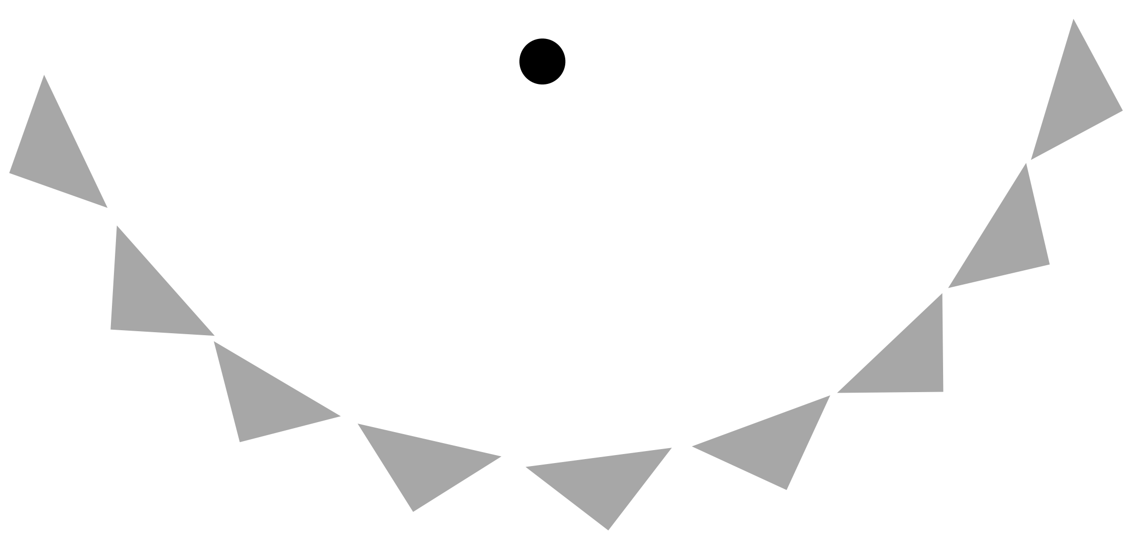
Which cameras are observing which points at each time?

# Time-varying Visibility Reasoning

## Why Is It Important in Dynamic 3D Reconstruction?

**Static Scene**

Point cloud reconstruction



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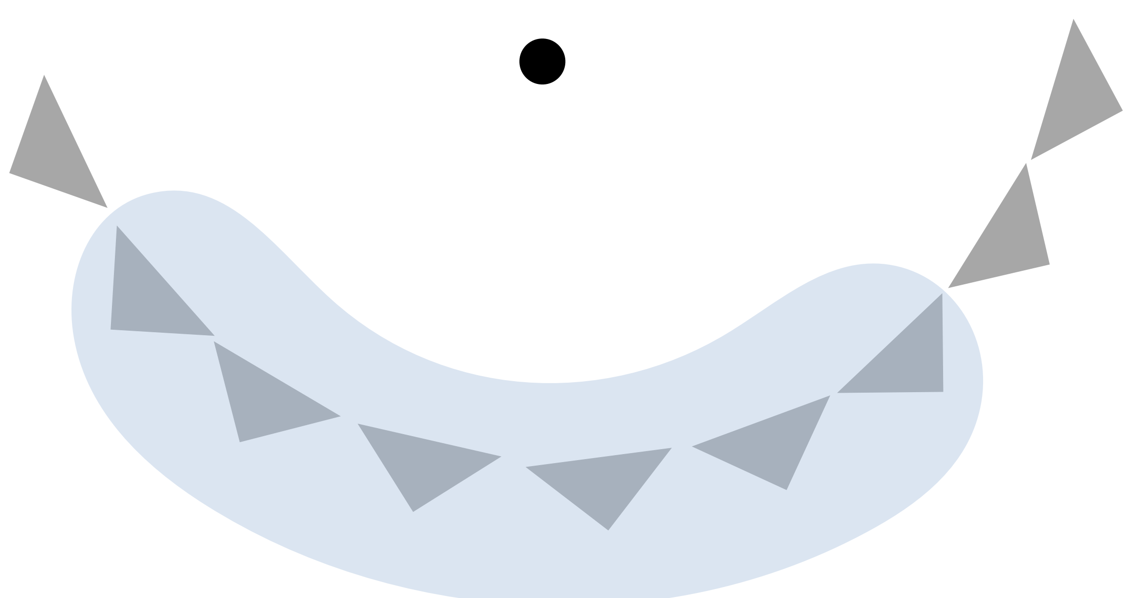

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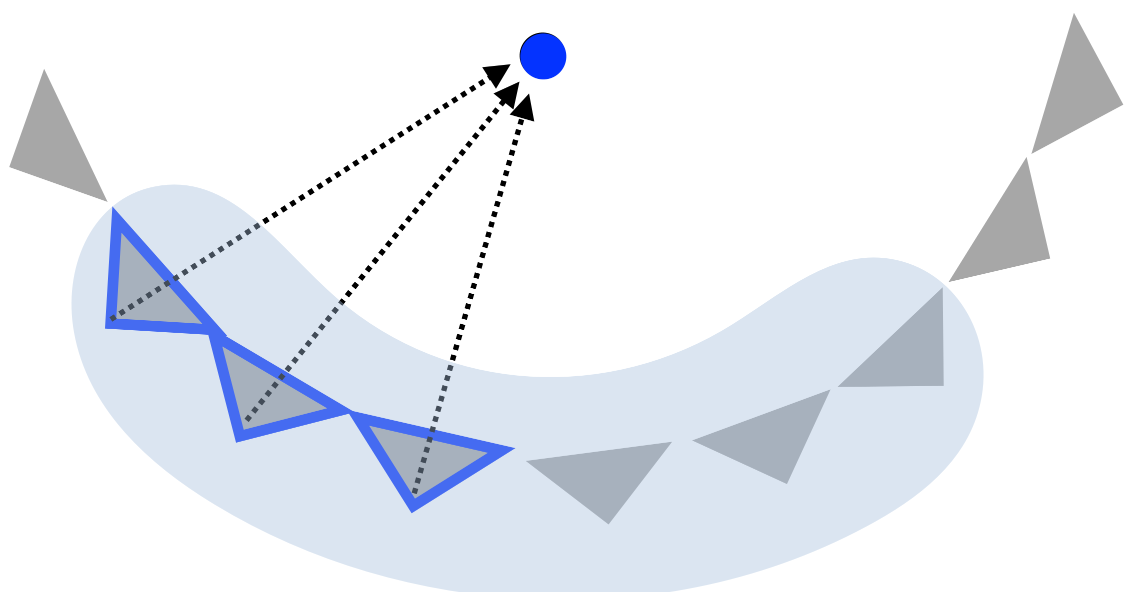

Error in visibility reasoning

# Time-varying Visibility Reasoning

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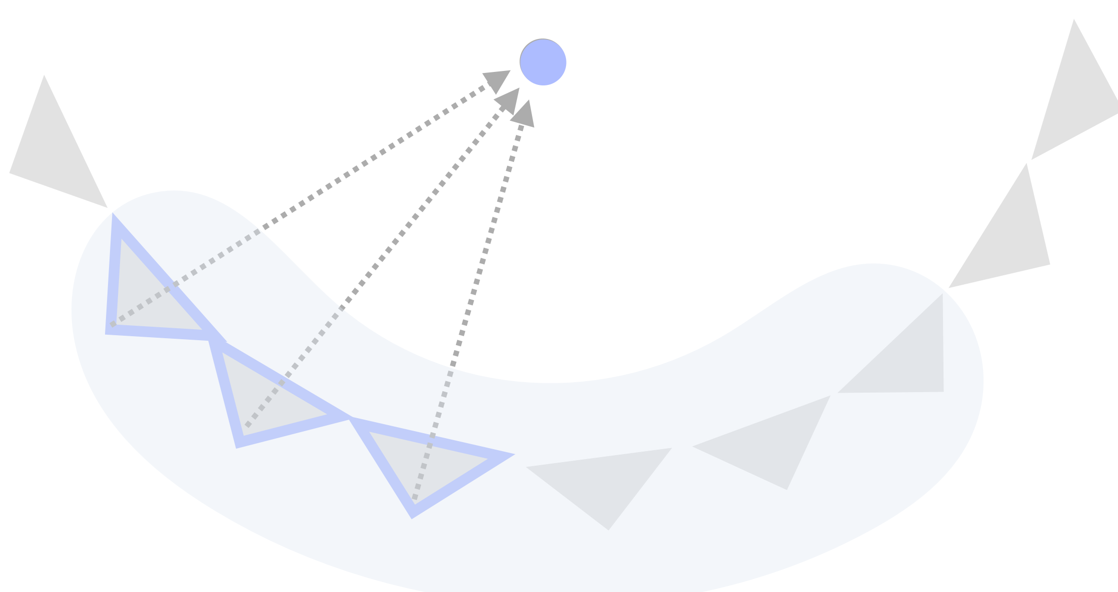
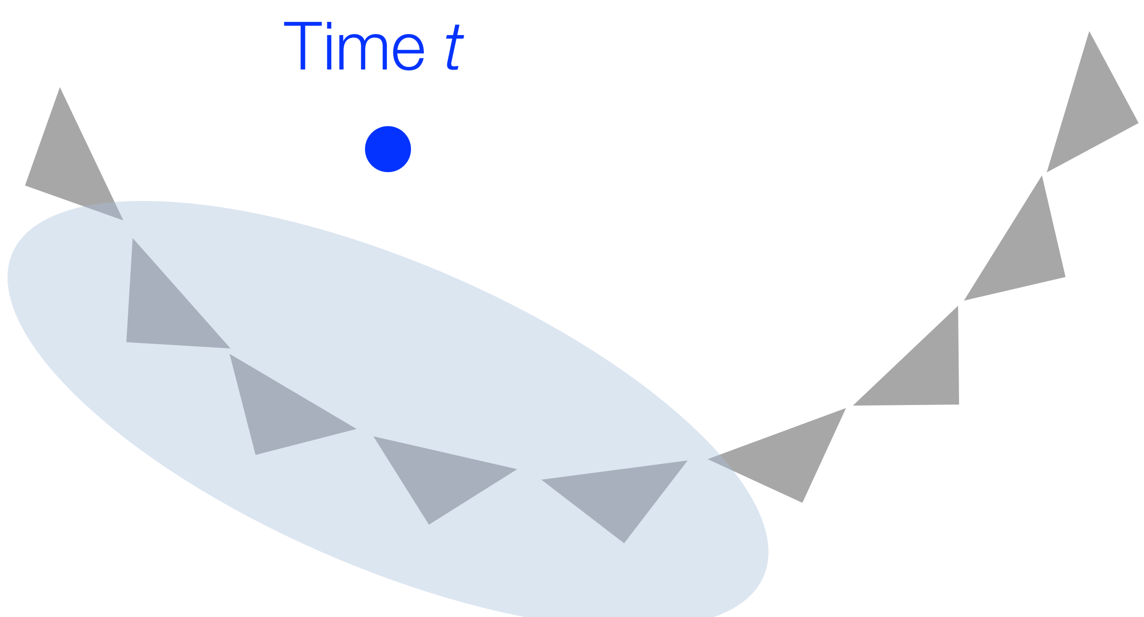


**Dynamic Scene**

Trajectory stream reconstruction



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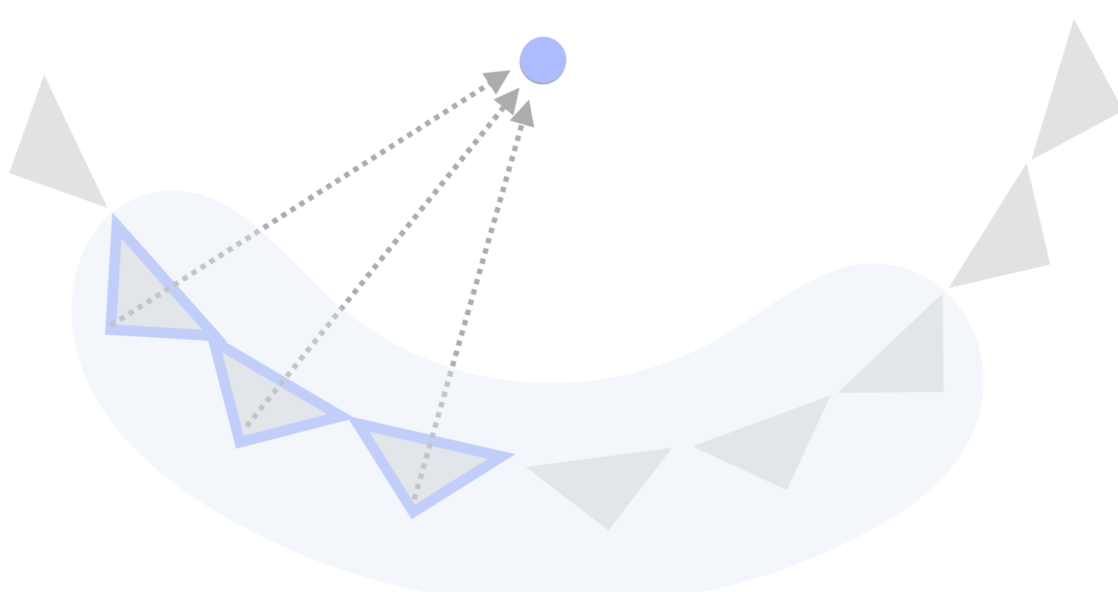
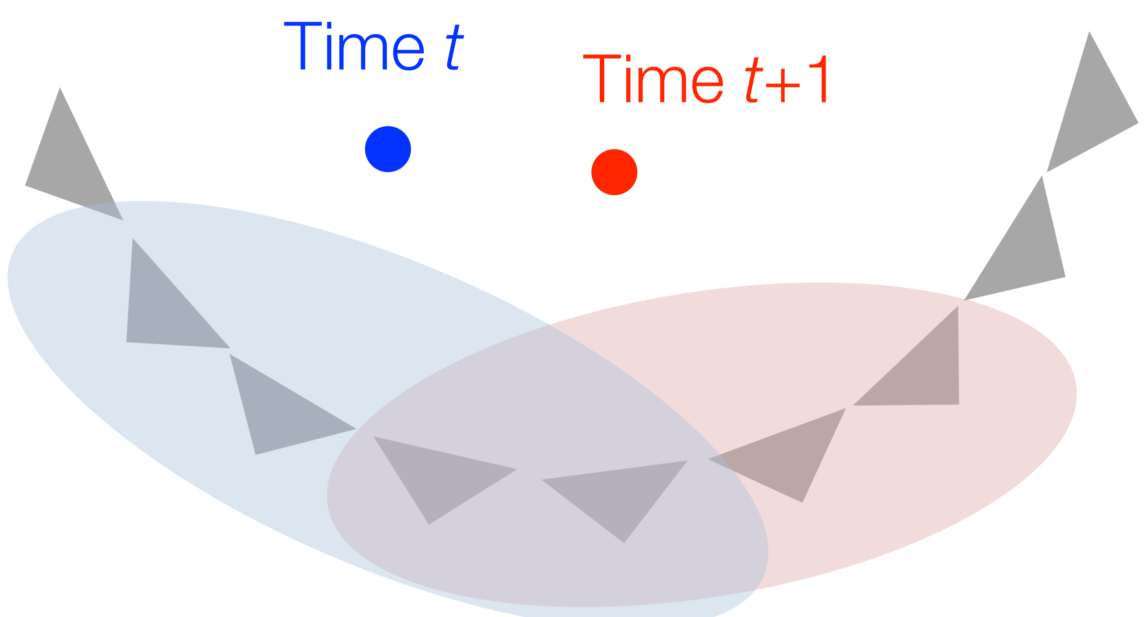


**Dynamic Scene**

Trajectory stream reconstruction



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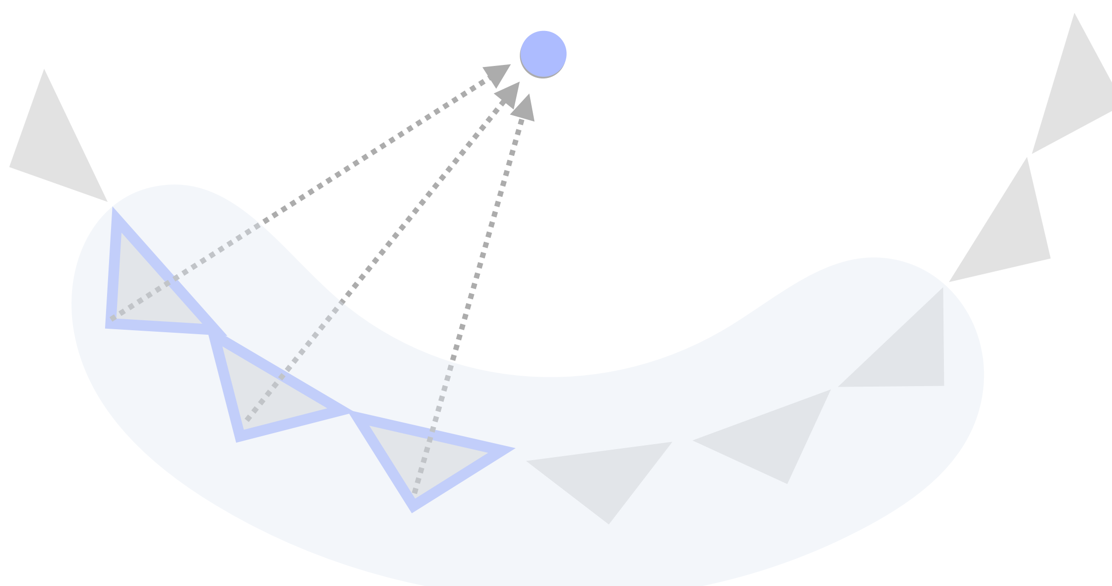
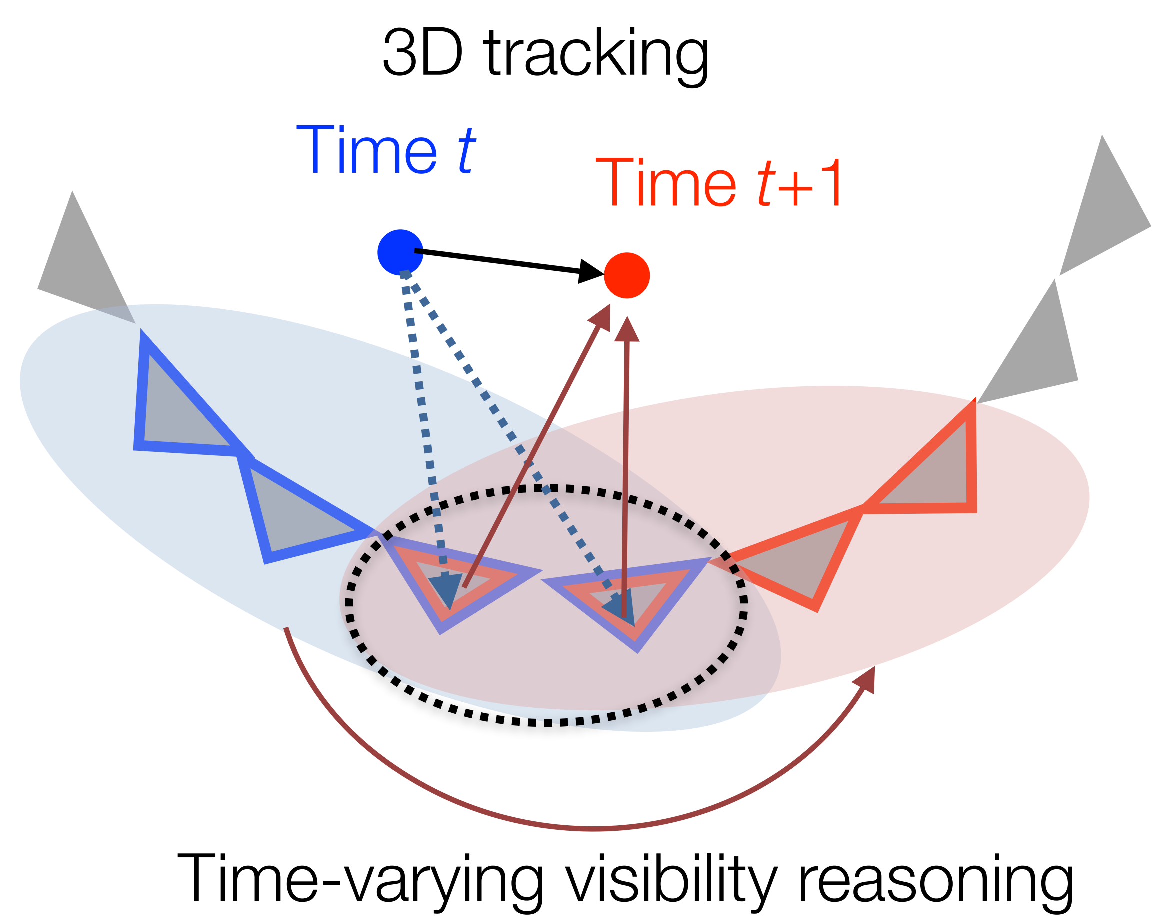
Point cloud reconstruction



**Dynamic Scene**

Trajectory stream reconstruction



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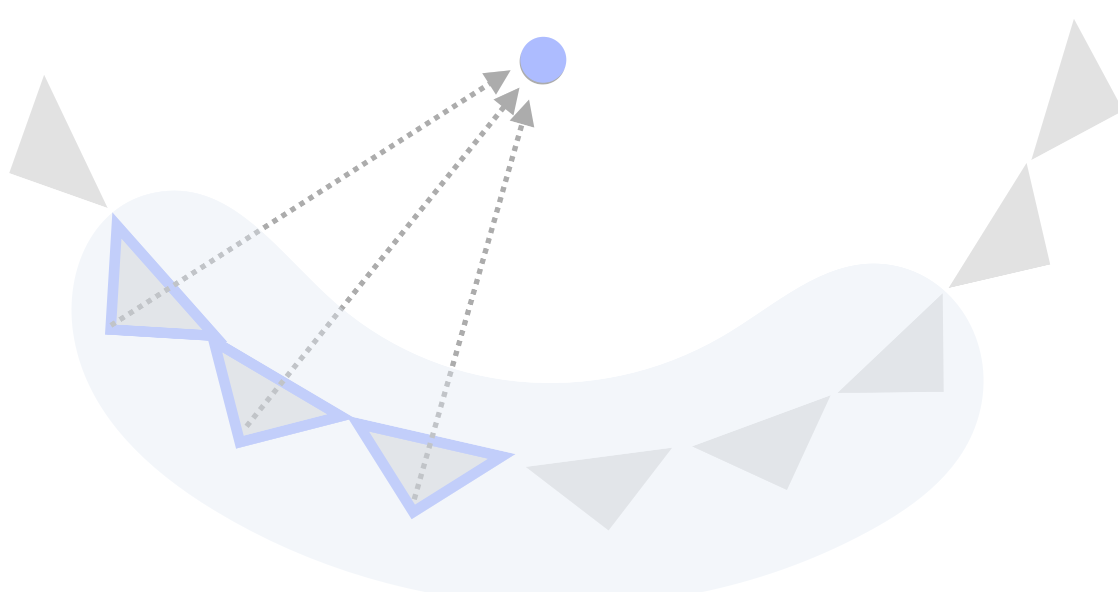
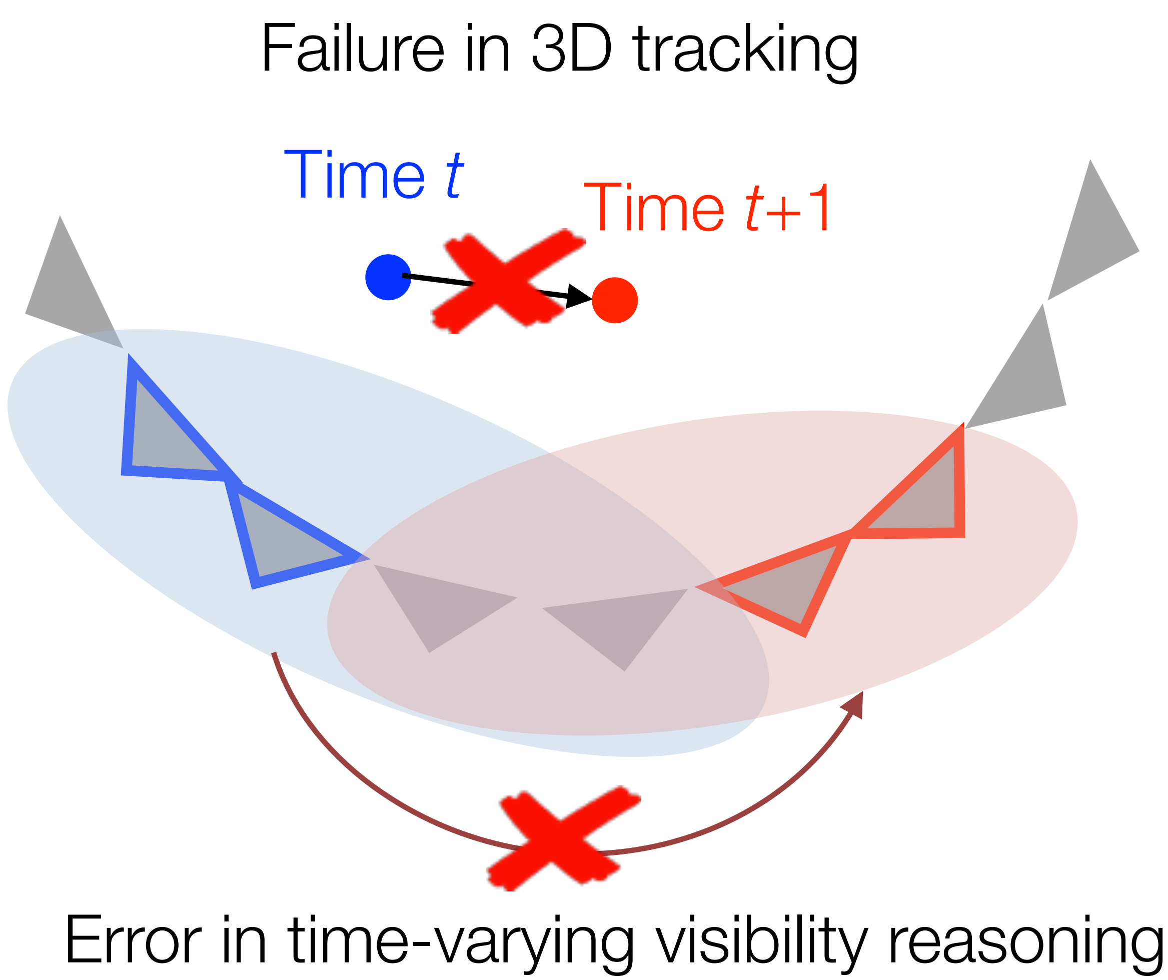


**Dynamic Scene**

Trajectory stream reconstruction

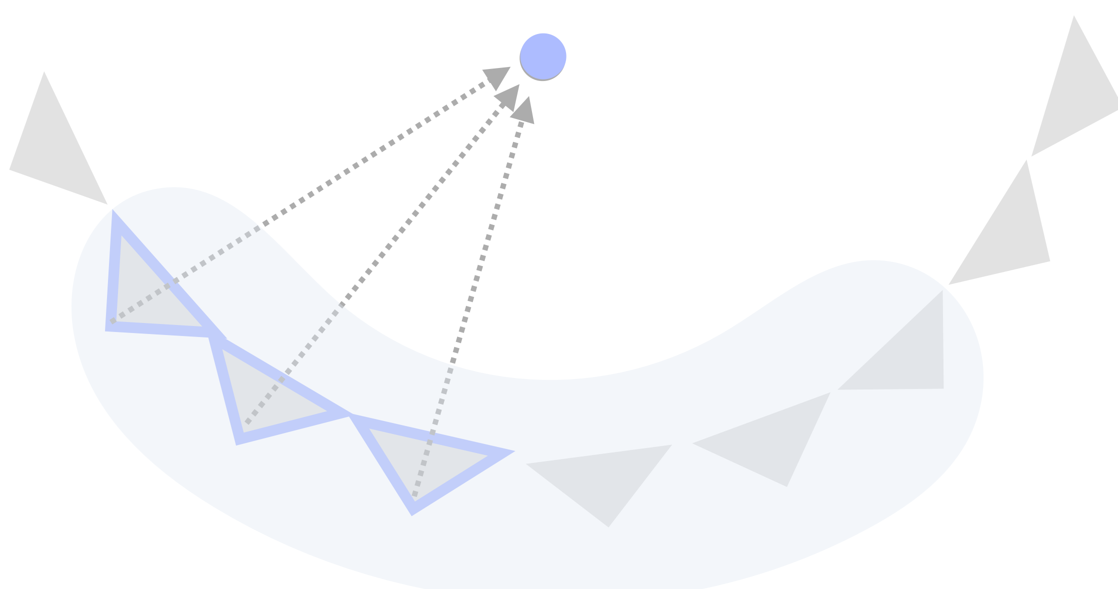


# Time-varying Visibility Reasoning

## Why Is It Important in Dynamic 3D Reconstruction?

**Static Scene**

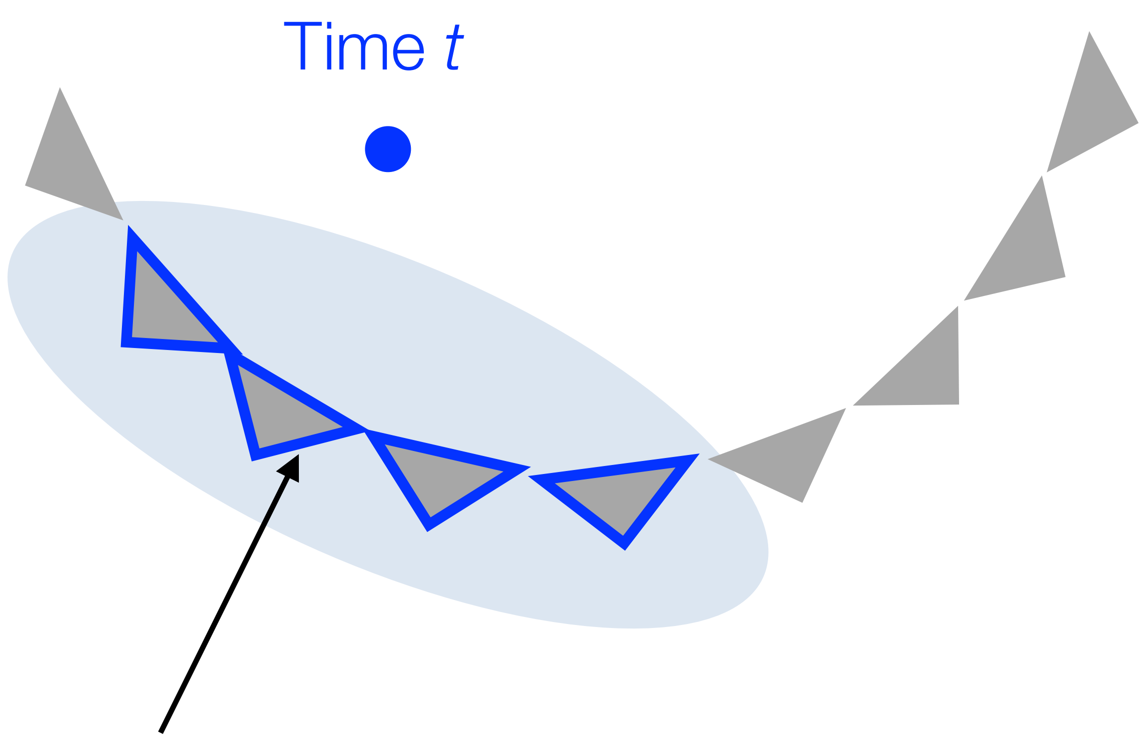
Point cloud reconstruction



**Dynamic Scene**

Trajectory stream reconstruction

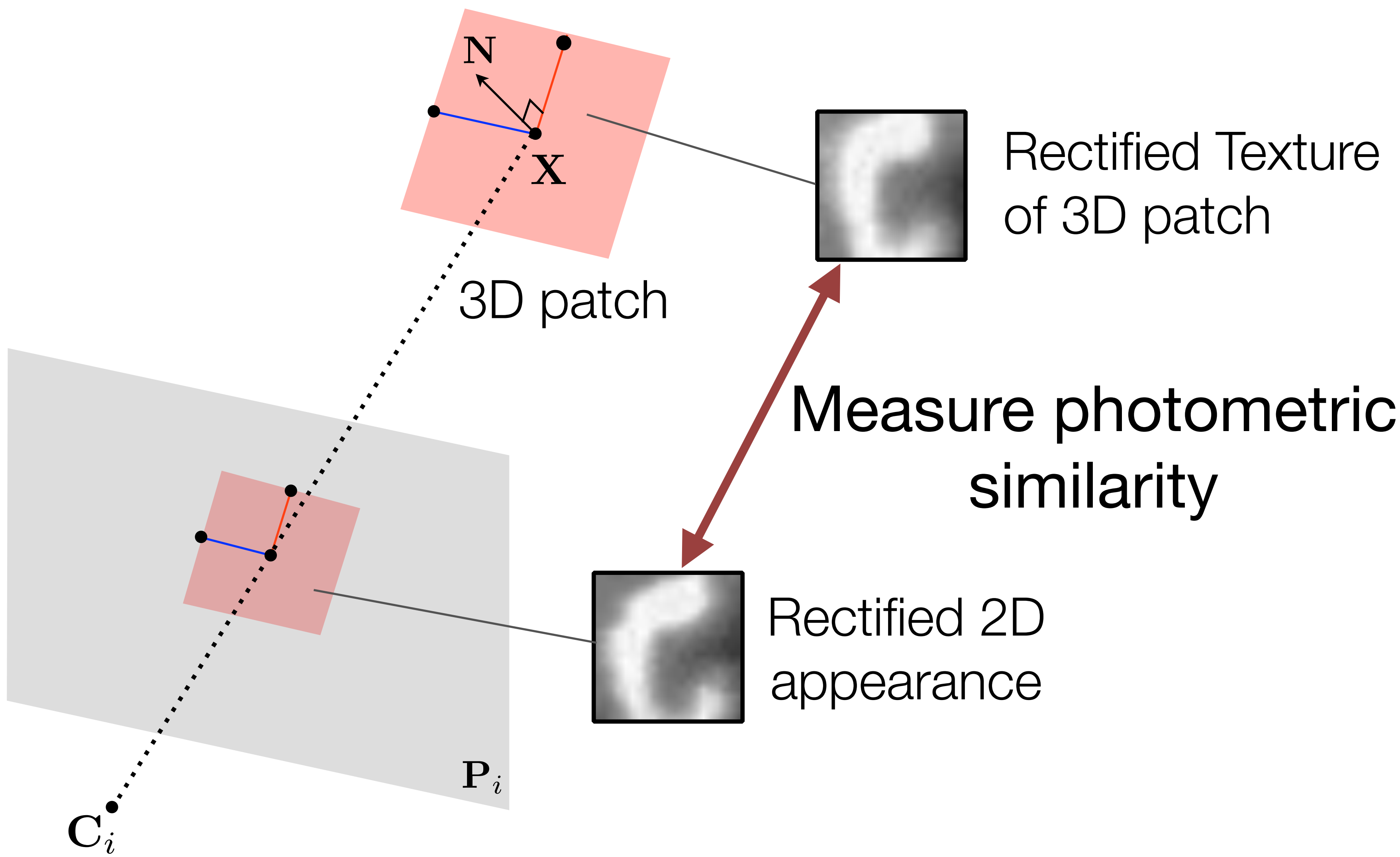
Failure in 3D tracking




As large and accurate visibility set as possible

# Photometric Consistency

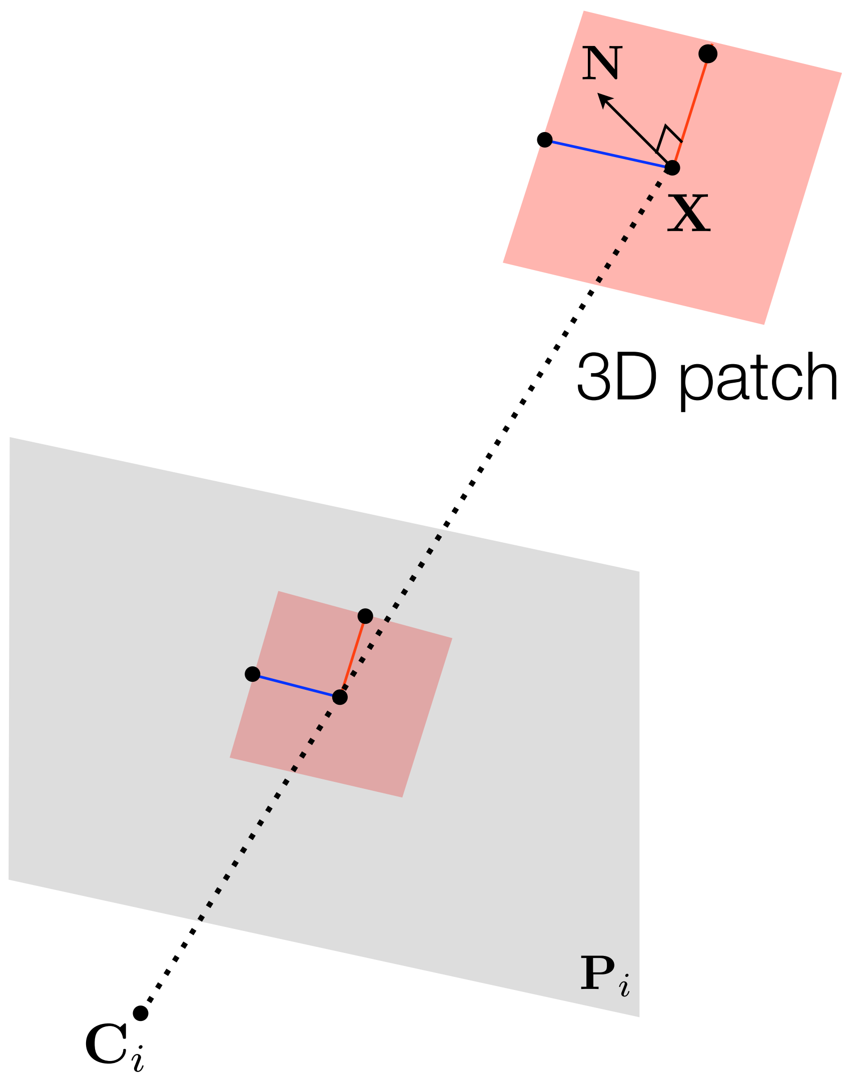
## A Common Cue for Static Scene Reconstruction

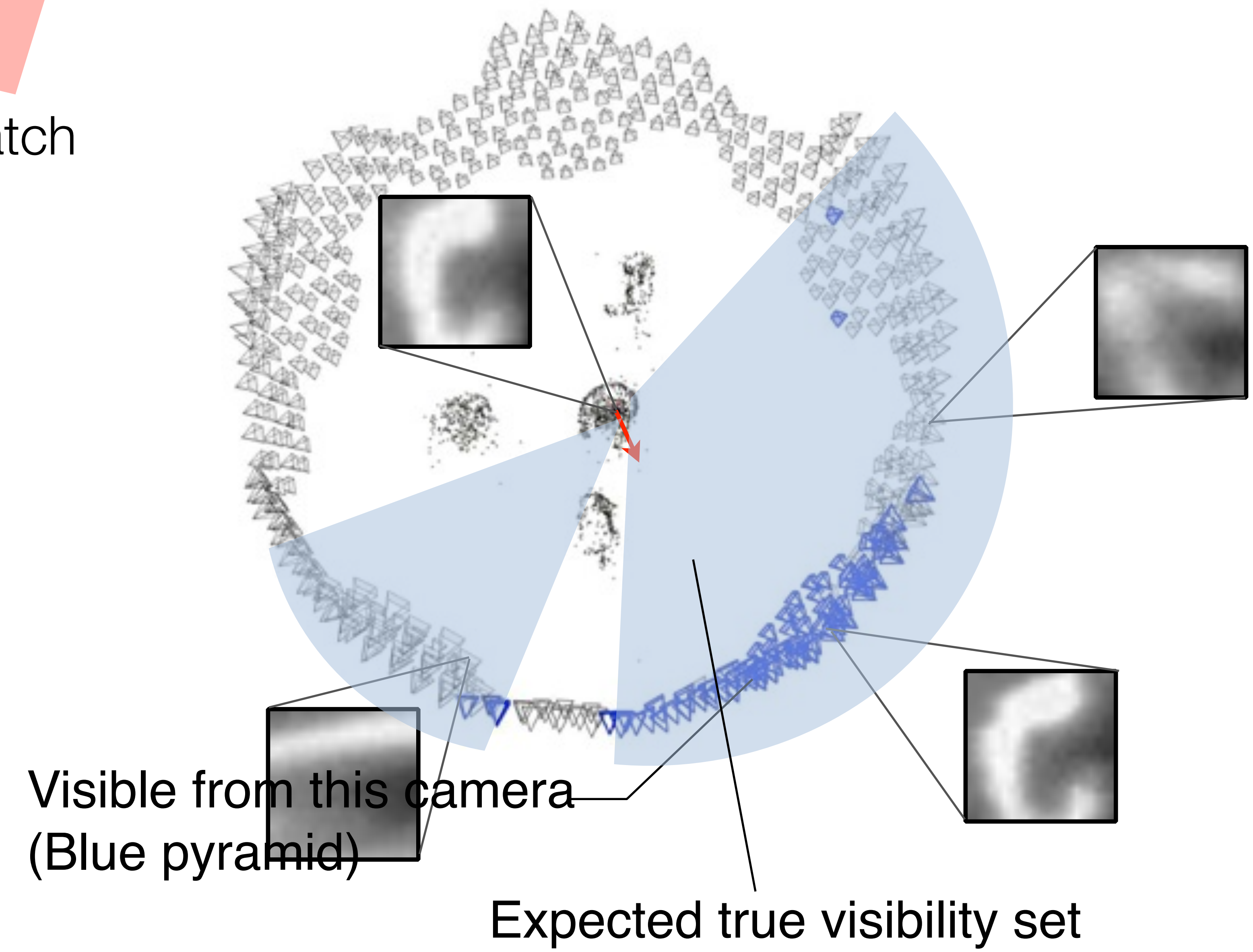



Accurate 3D patch shape and its texture are required

# Photometric Consistency

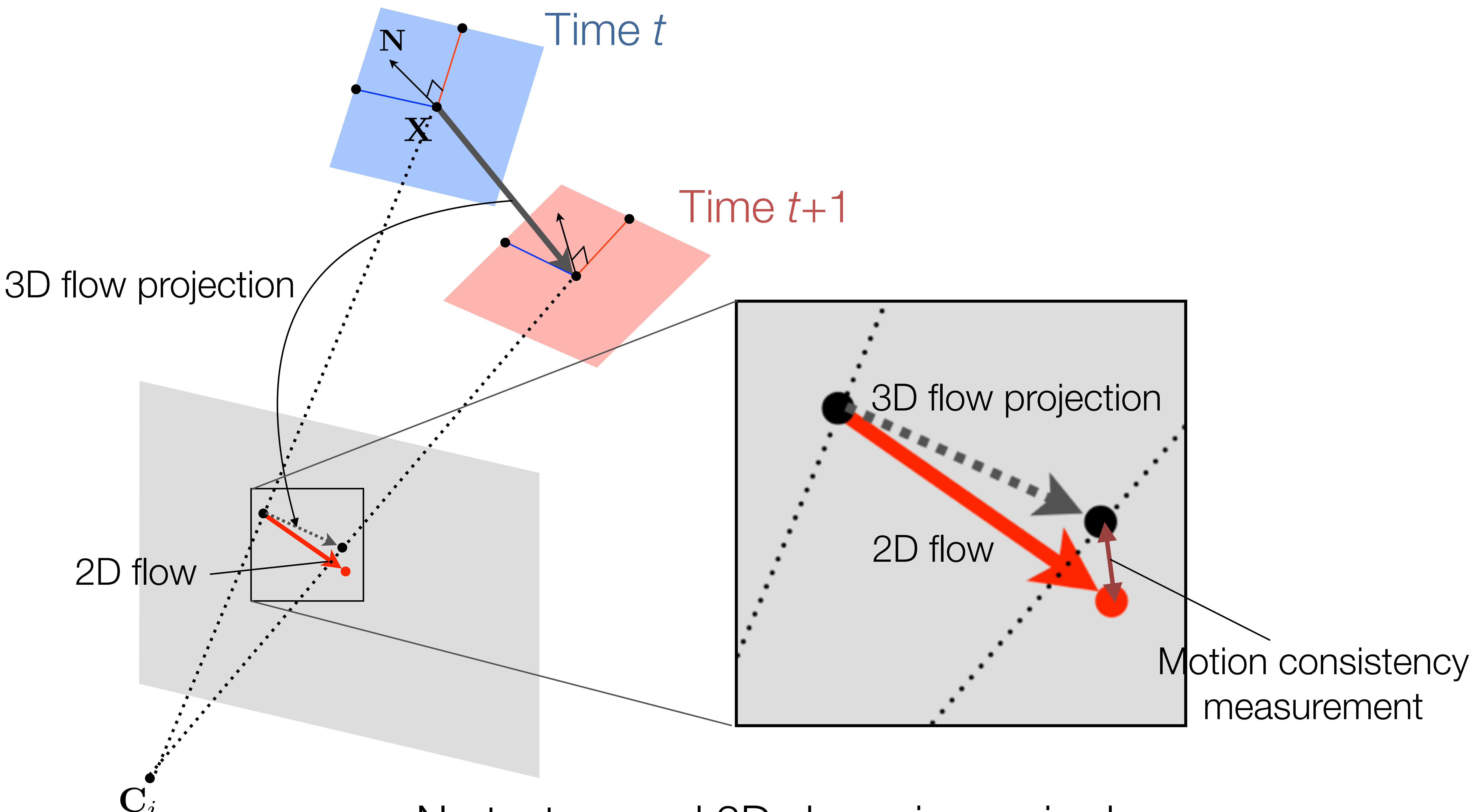
## A Common Cue for Static Scene Reconstruction



# Motion Consistency

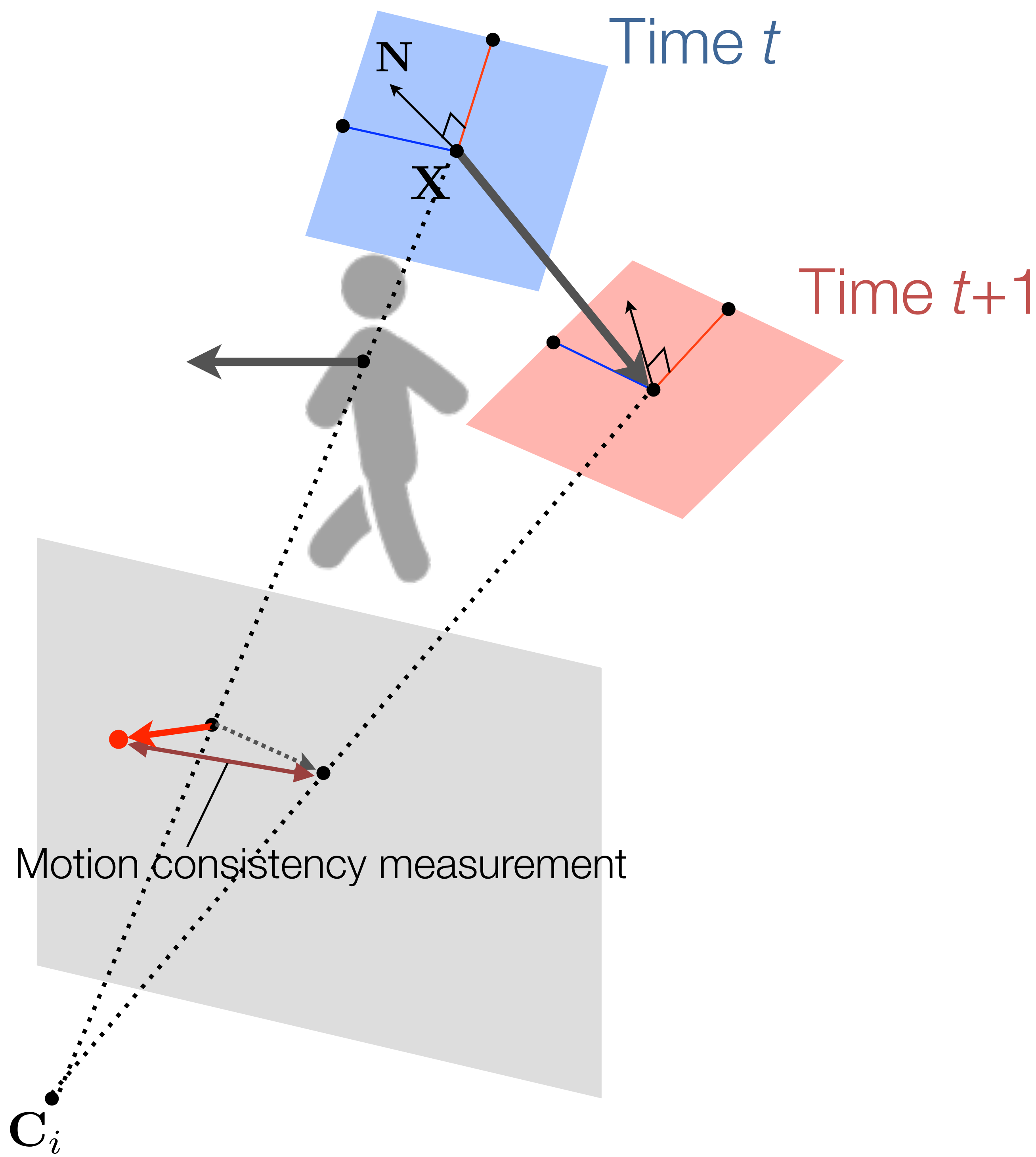
## A Novel Cue in Dynamic Scene




No texture and 3D shape is required

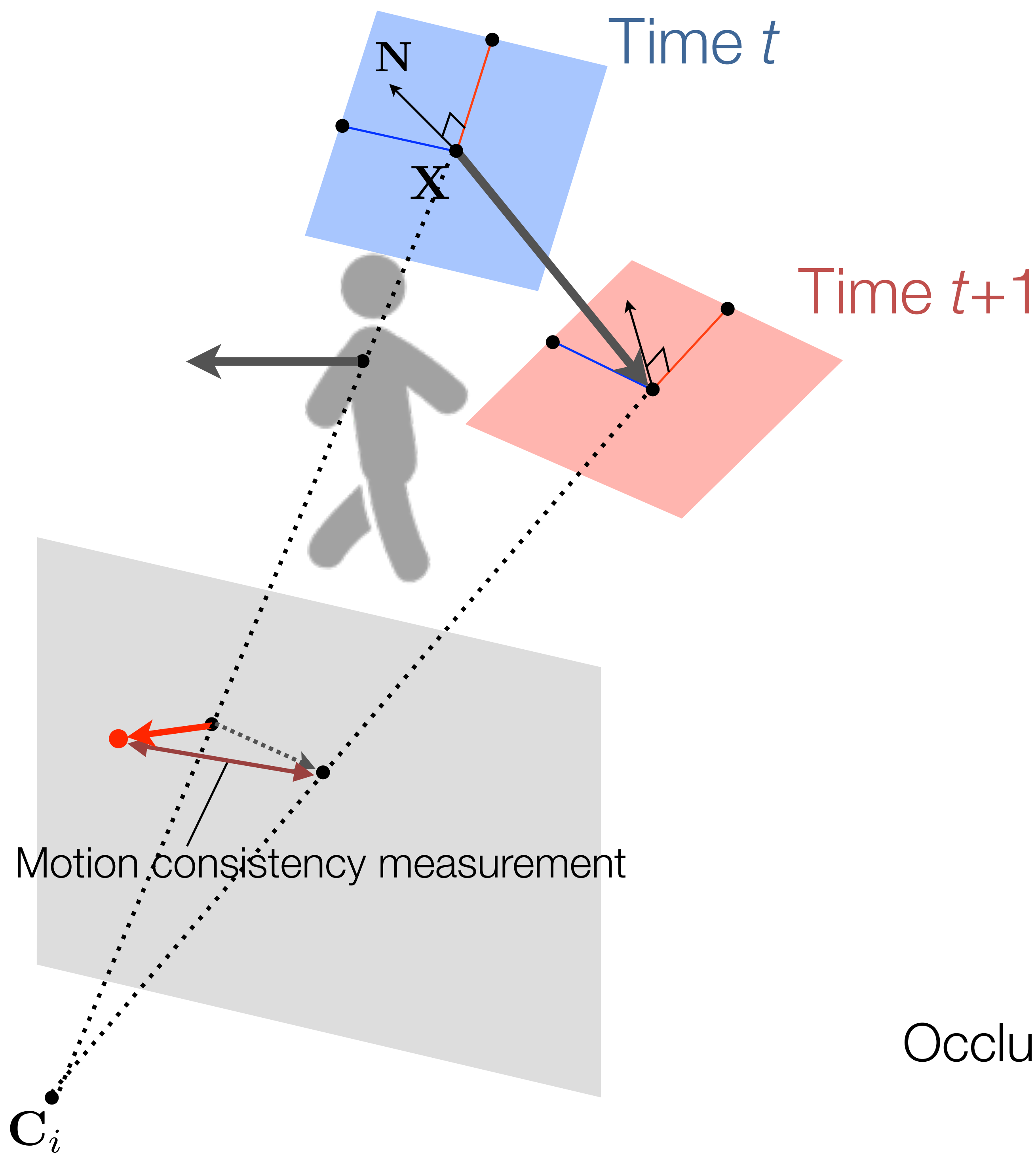
# Motion Consistency

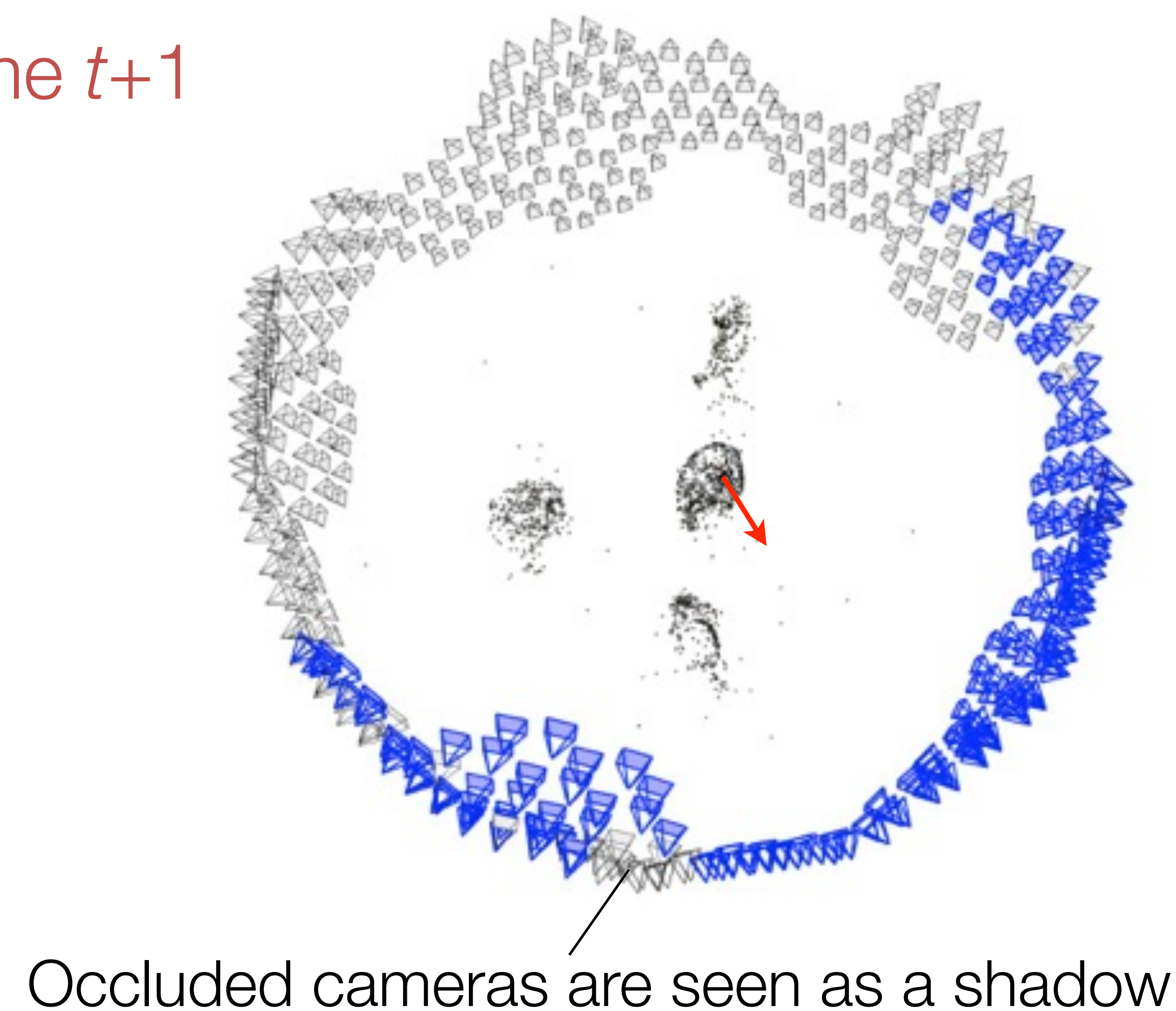
## A Novel Cue in Dynamic Scene



# Motion Consistency

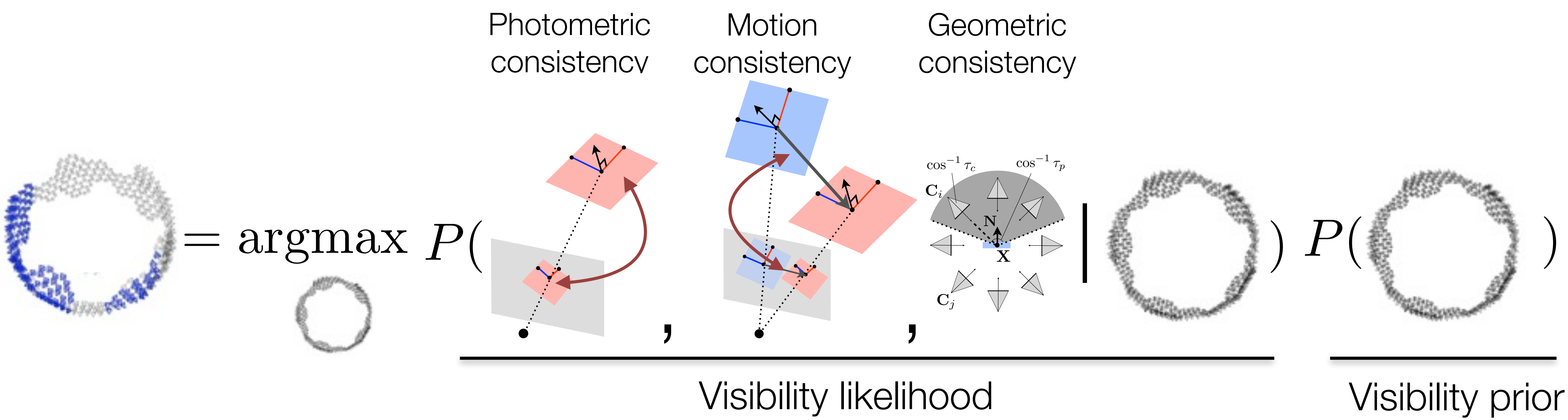
## A Novel Cue in Dynamic Scene



# MAP Visibility Estimate

## Visibility Likelihood and Visibility Prior



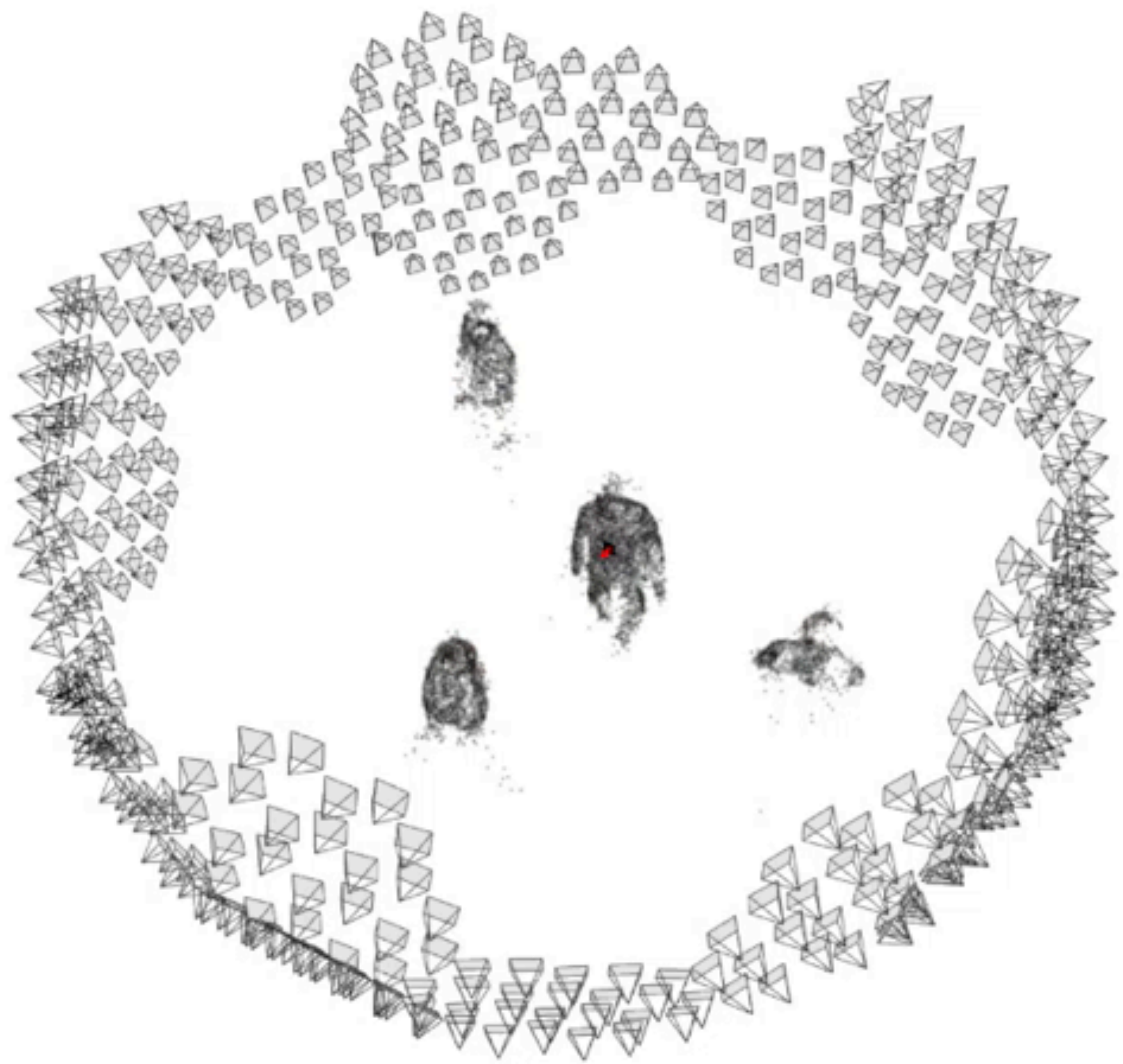
# Result

# Trajectory Stream Reconstruction Result

## The Circular Motion Sequence

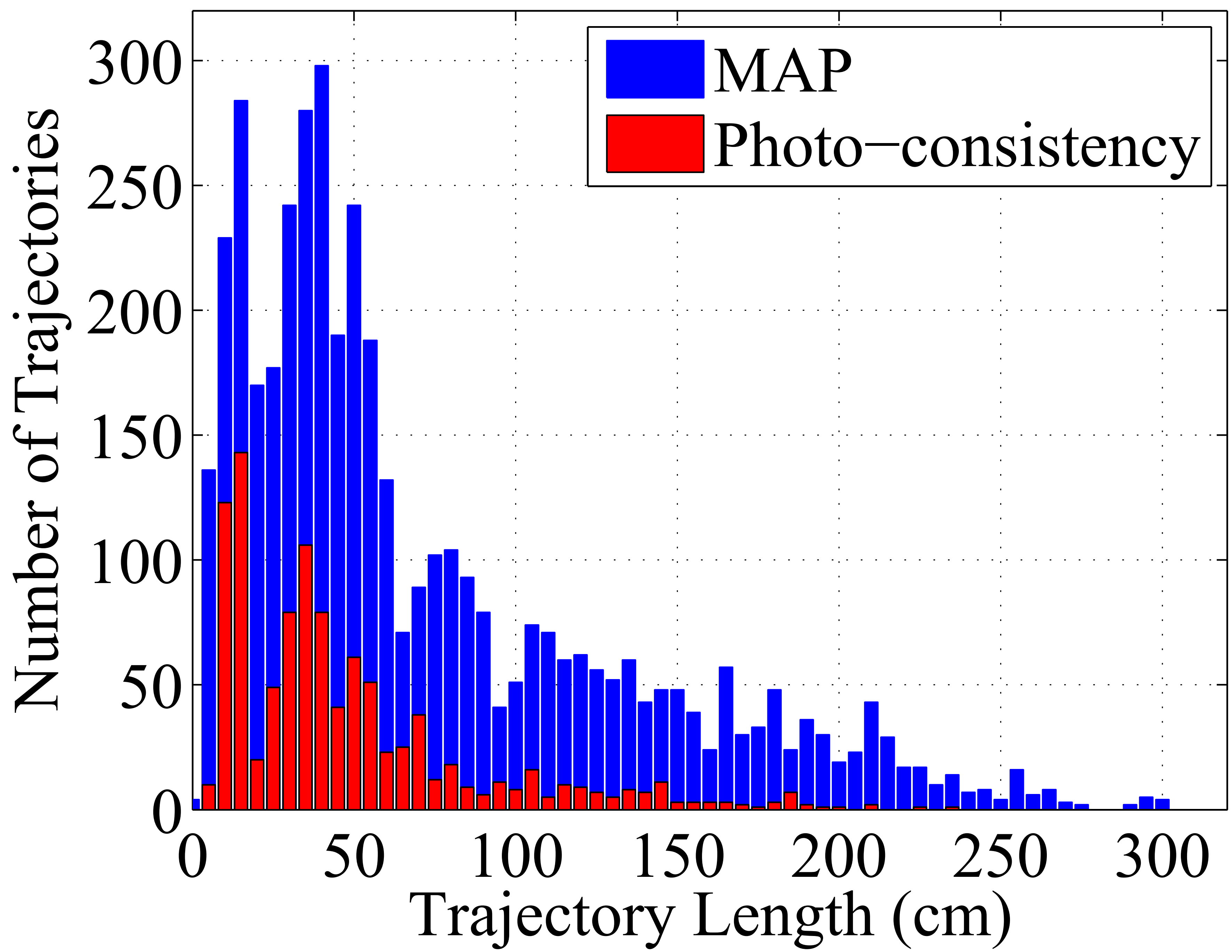
# Time-varying Visibility Reasoning

## Our Result



# Dynamic 3D Reconstruction Result

## Quantitative Comparison

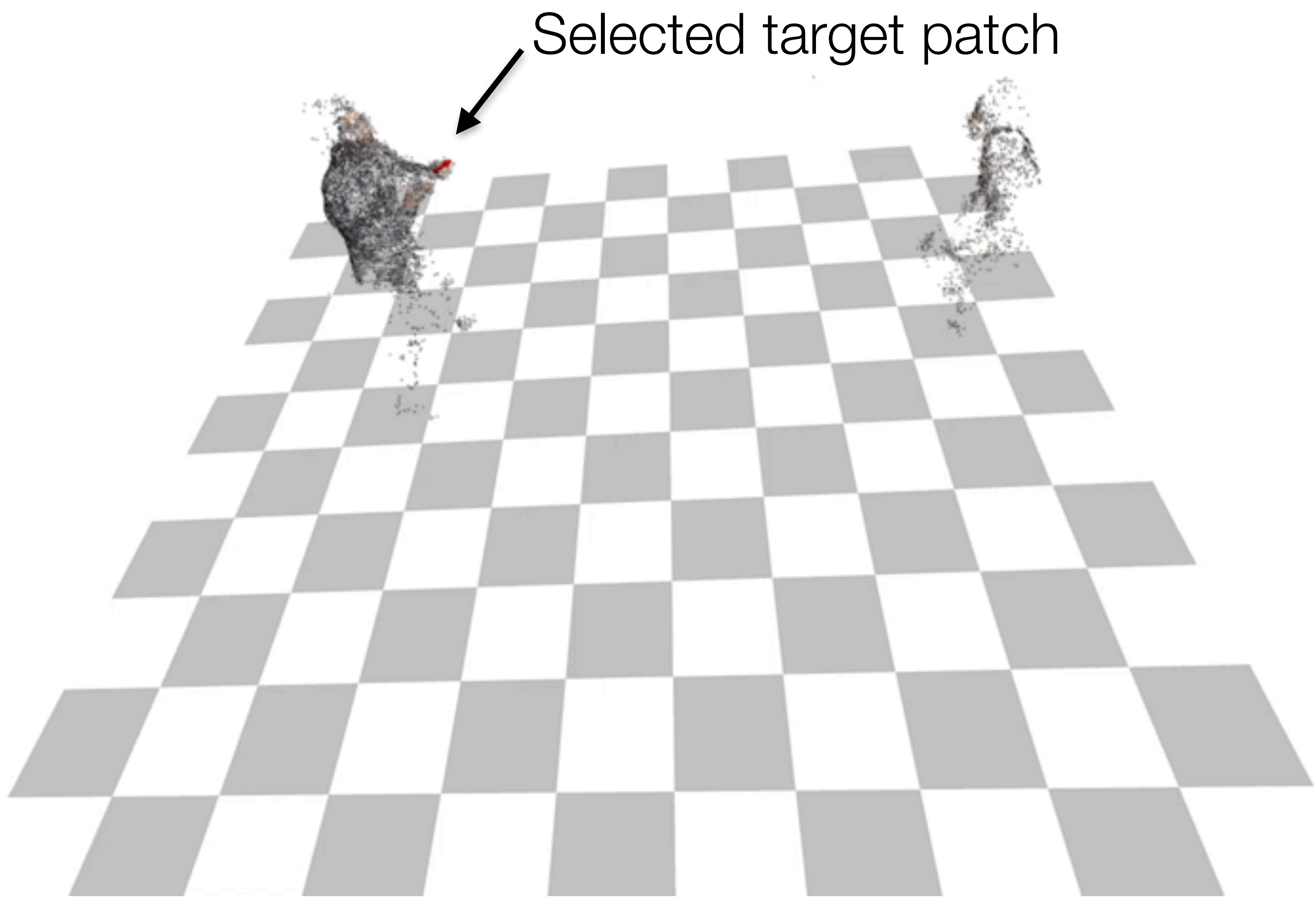


# Trajectory Stream Reconstruction Result

## The Volleyball Sequence

# Trajectory Stream Reconstruction Result

## The Volleyball Sequence: a Detail View



# Trajectory Stream Reconstruction Result

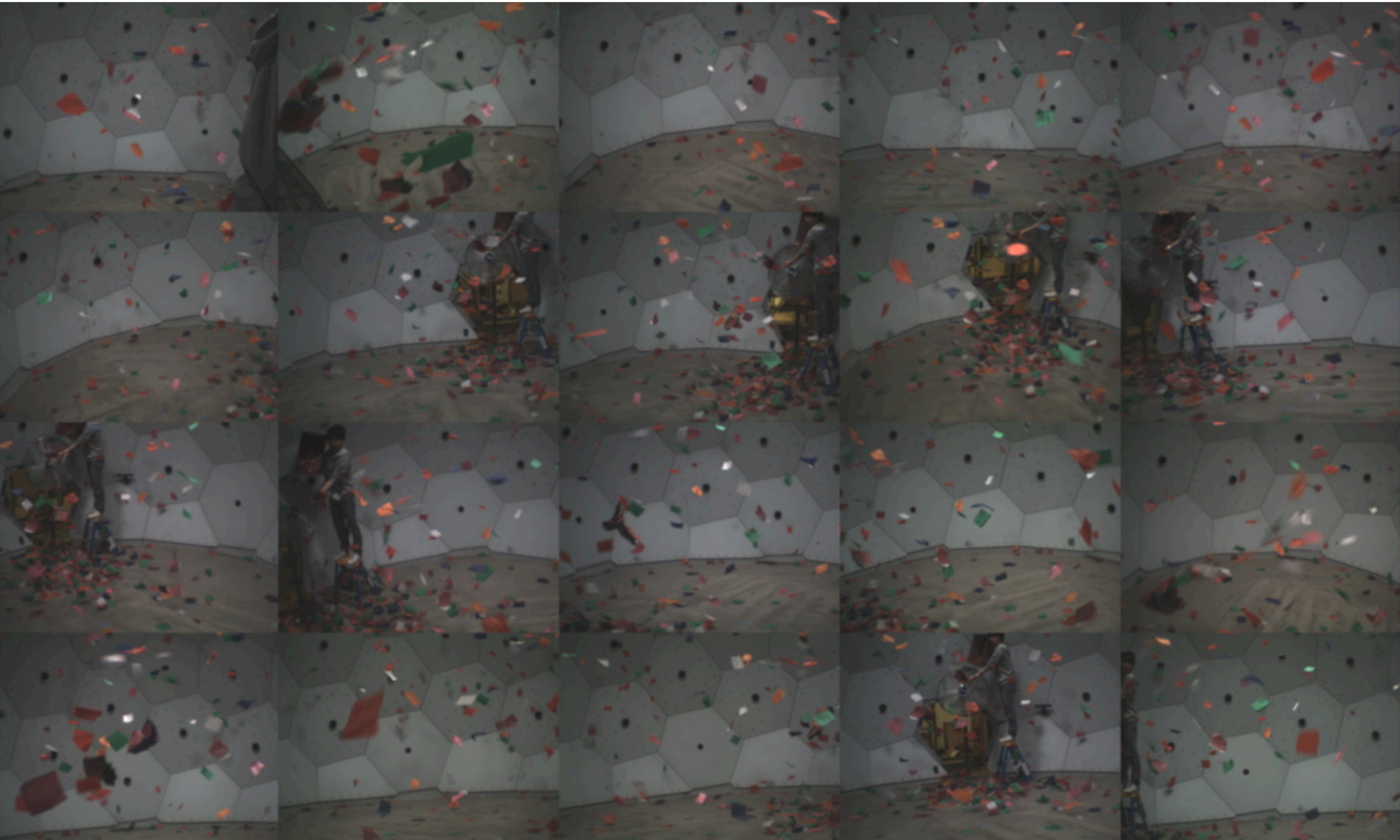
## The Falling Boxes Sequence

# Trajectory Stream Reconstruction Result

## The Confetti Sequence

# Trajectory Stream Reconstruction Result

## The Fluid Motion Sequence



# Future Work

Moving cameras

Motion analysis

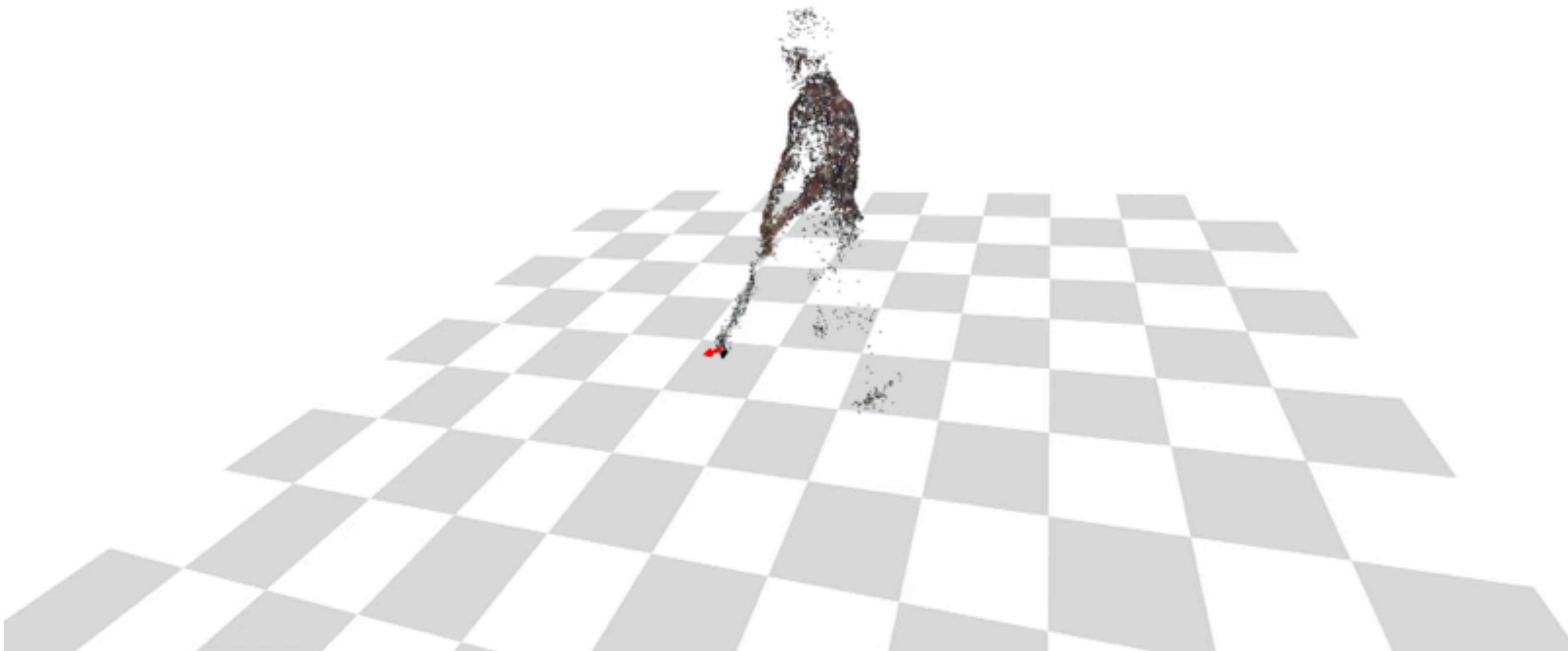
Social interactions

# Thank you

Please visit our poster (O-2A-5)

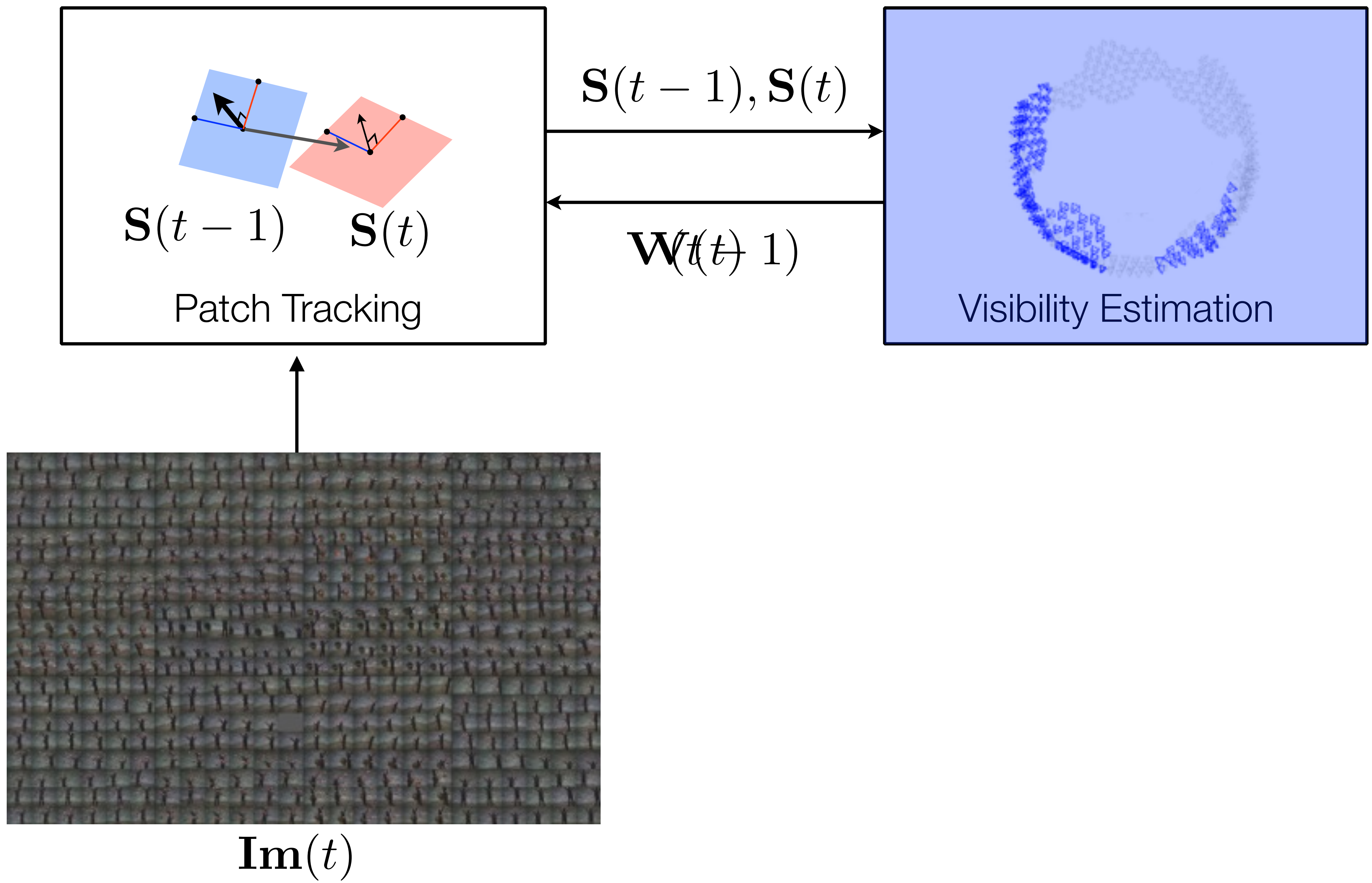
Dataset will be available at our project website:

http://www.cs.cmu.edu/~hanbyulj/14/visibility.html

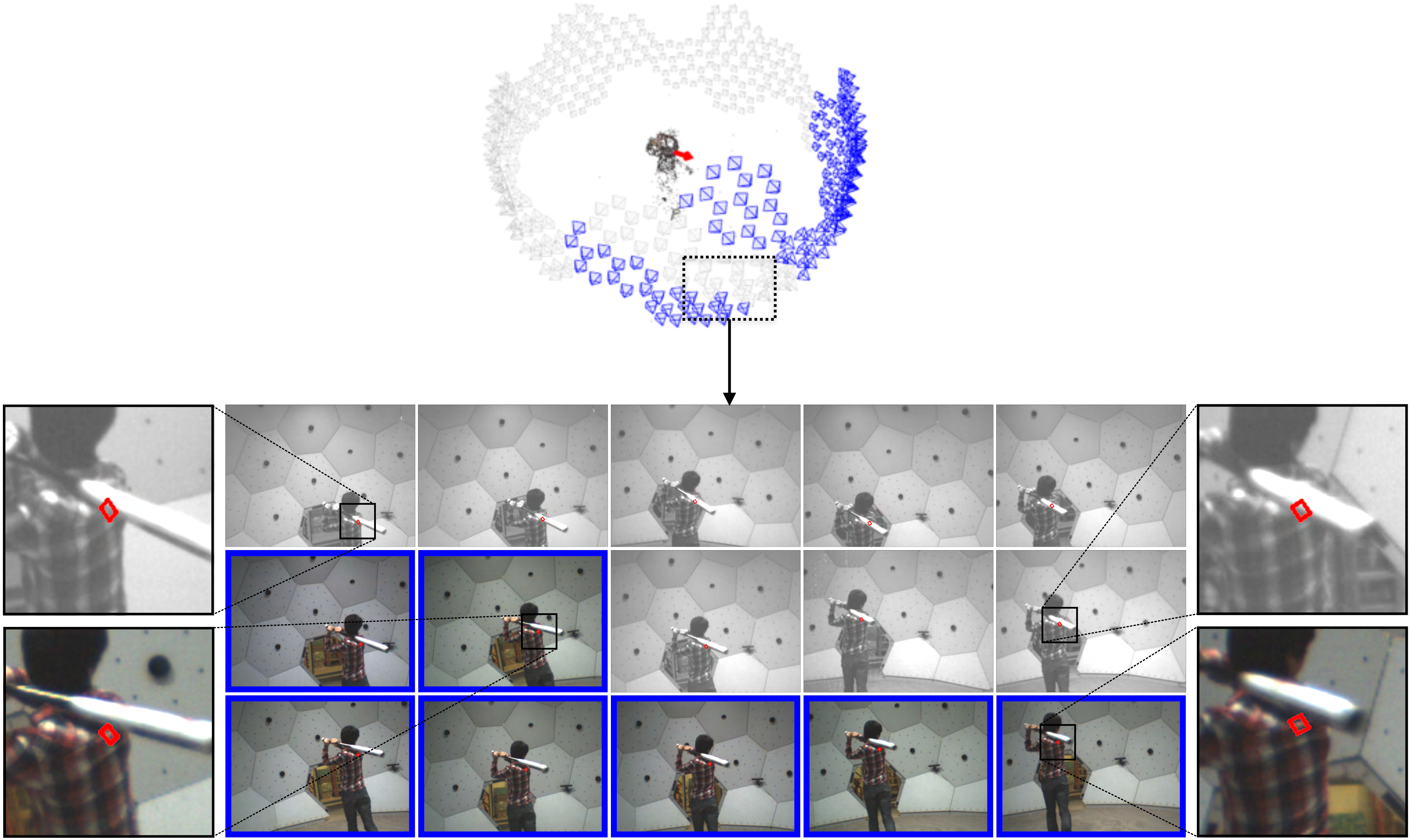


# Backup Slides

# Algorithm Overview
## Patch Tracking and Visibility Estimation

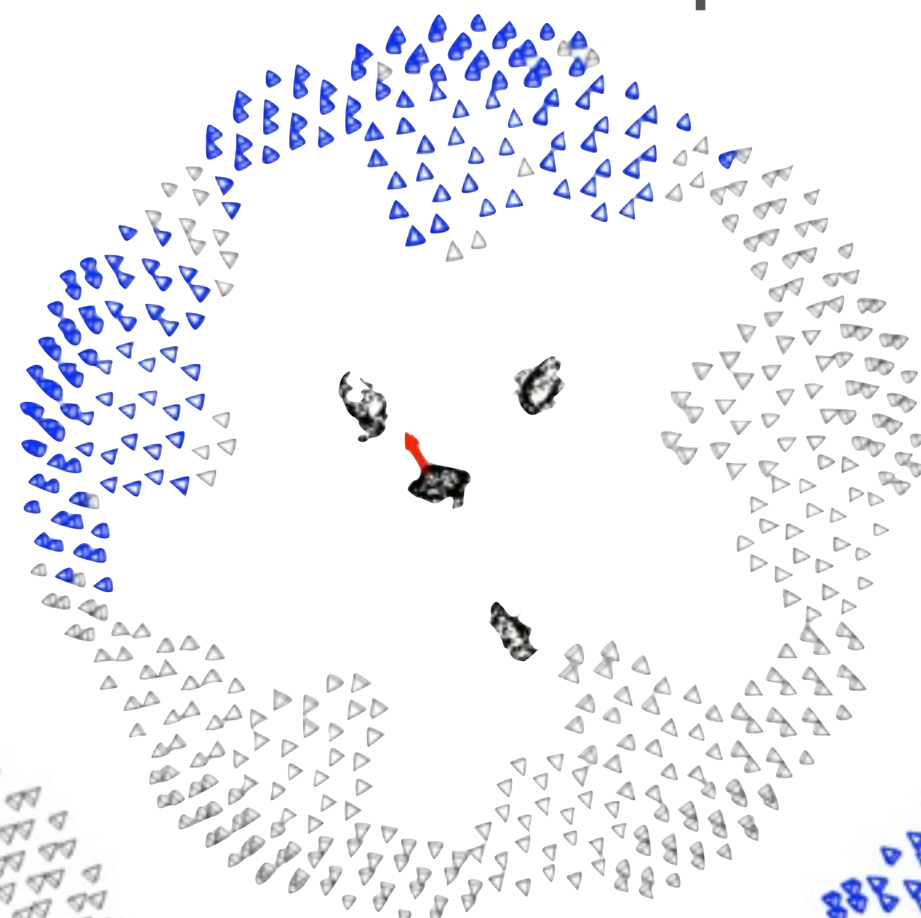


# Detailed Views of Visibility Reasoning Result

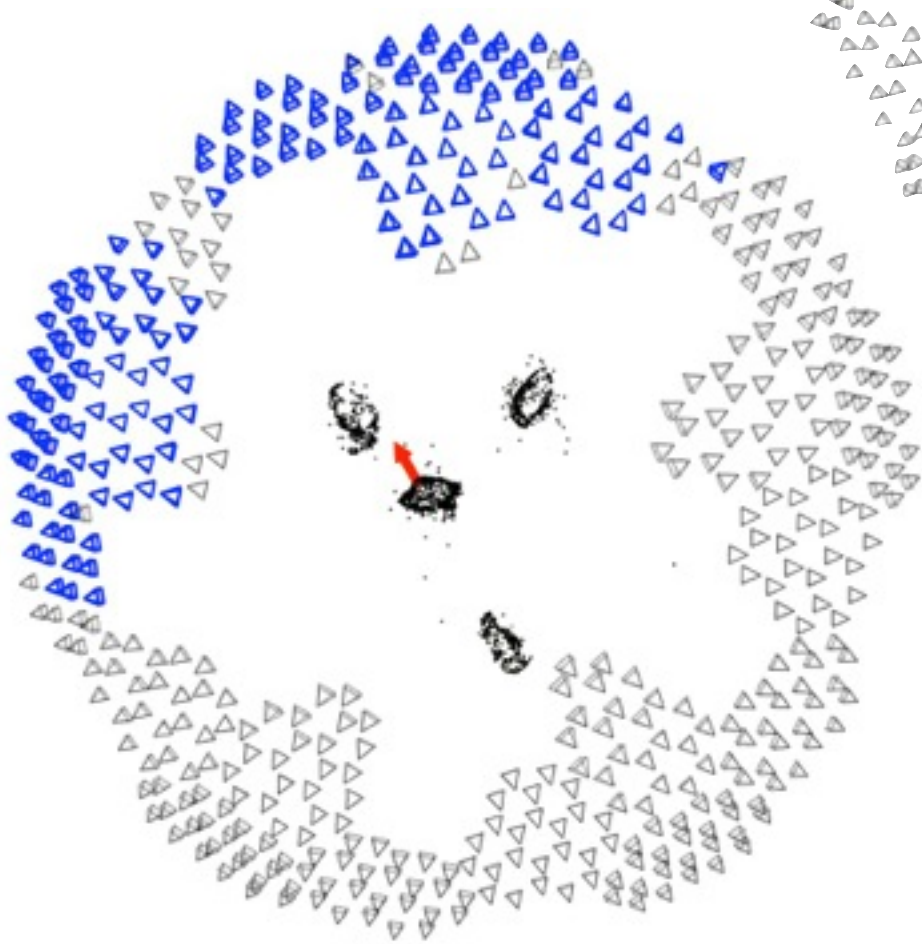


# Visibility Reasoning Result

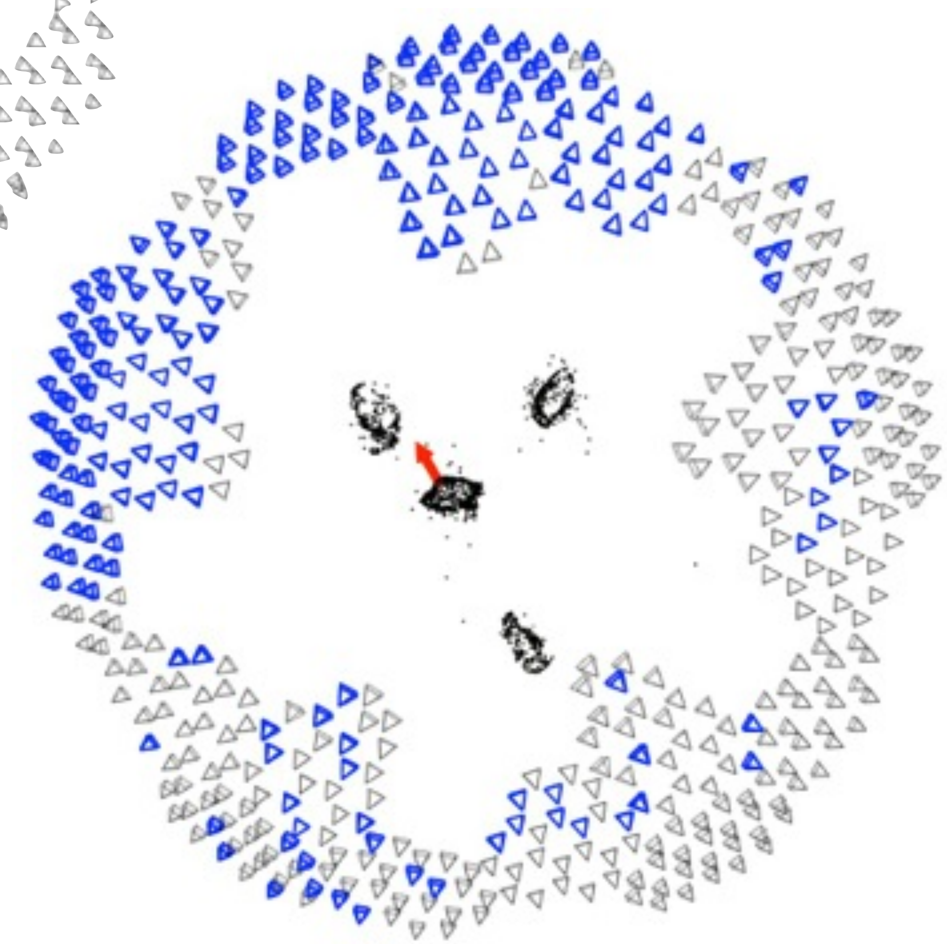
## Qualitative Comparison



Ground truth



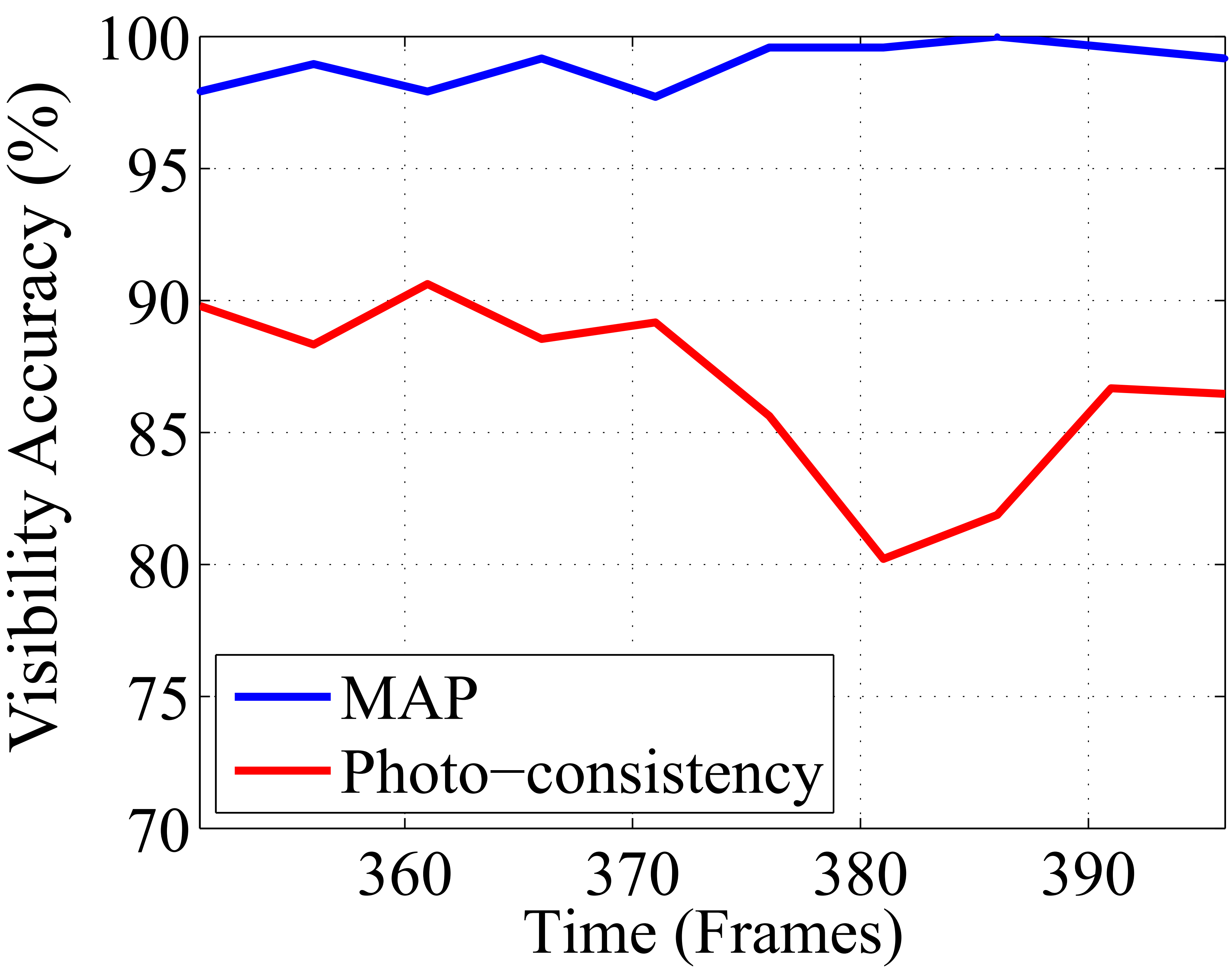
Our method



Photometric consistency

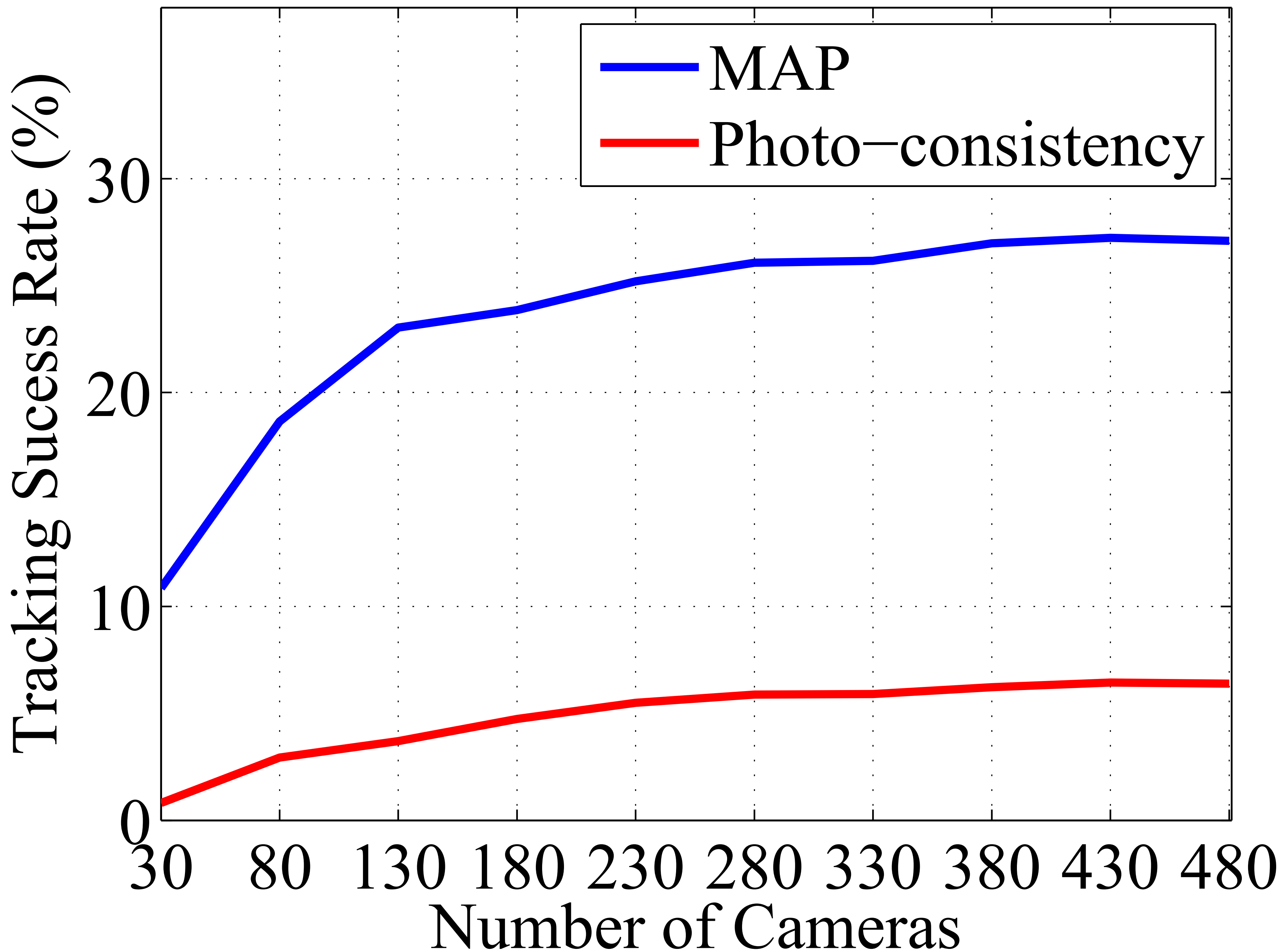
# Visibility Reasoning Result

## Quantitative Comparison



# Dynamic 3D Reconstruction Result

## Quantitative Comparison



# Summary of the Datasets

| Sequence | Frames | Duration | # of points | Av. traj. length |
|---|---|---|---|---|
| Circ. Movement | 250 | 10.0 sec | 10433 | 404.9 cm |
| Volleyball | 210 | 8.4 sec | 8422 | 326.4 cm |
| Bat Swing | 200 | 8.0 sec | 3849 | 224.1 cm |
| Falling Boxes | 160 | 6.4 sec | 17934 | 164.7 cm |
| Confetti | 200 | 8.0 sec | 10345 | 103.0 cm |
| Fluid Motion | 200 | 8.0 sec | 3153 | 123.1 cm |

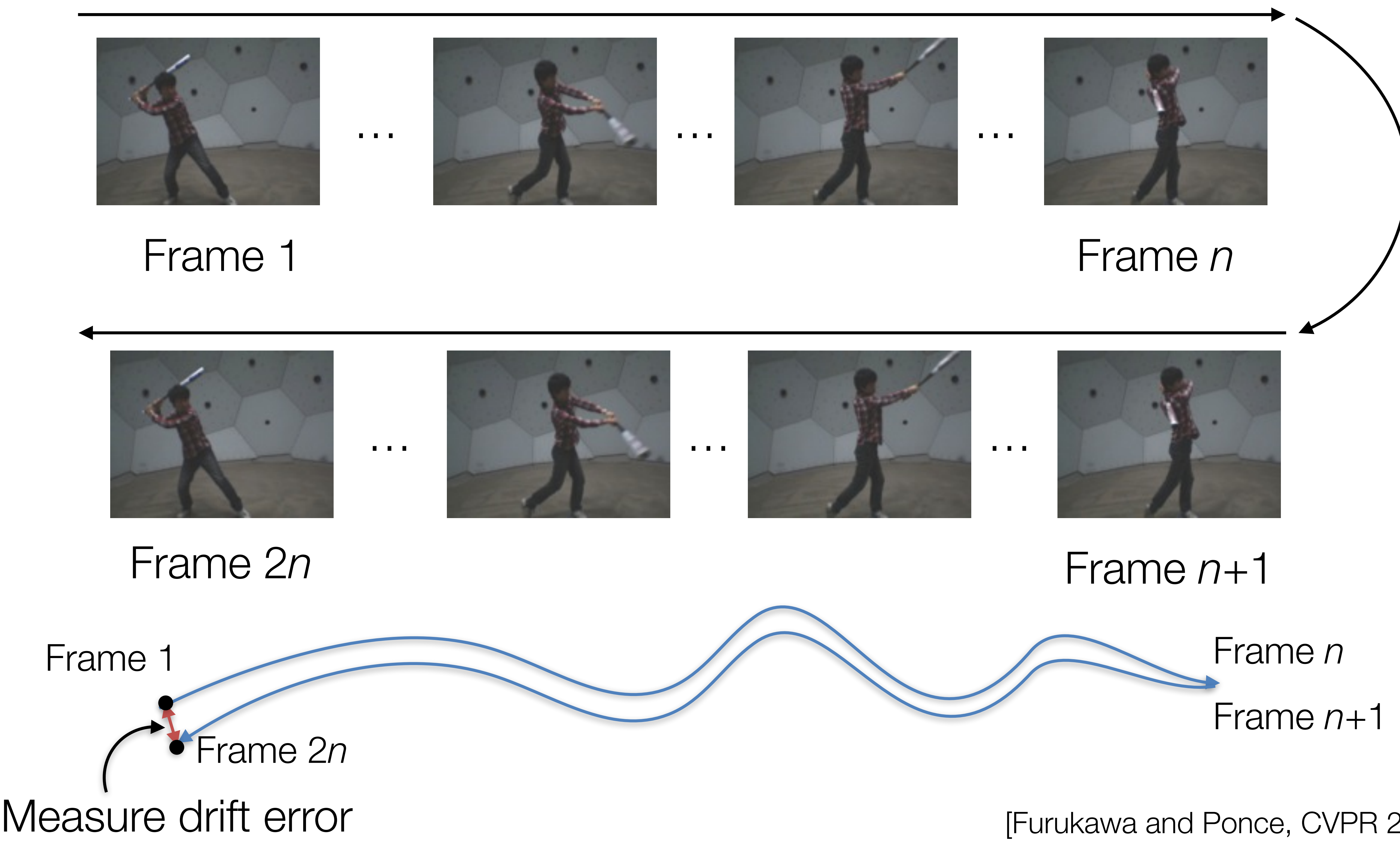
Trajectory reconstruction
from one time instance

Frame rate: 25frame / sec
Data size: 220GB / min

# Computation Time

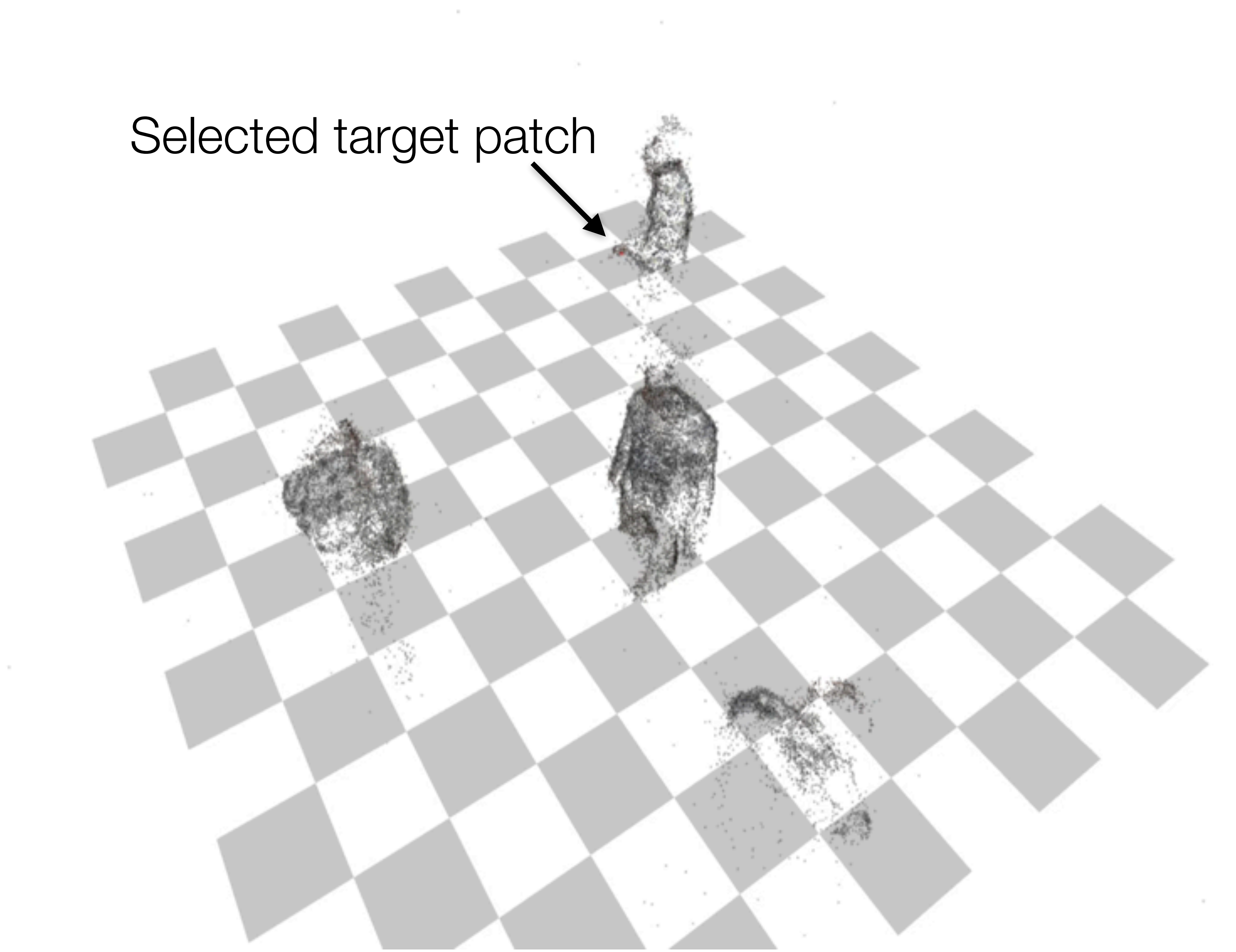
- 10,000 points over 8 sec
- Using 100 cores
- 12 hours
- 10~15 starting frames for each sequence — 1 week

# Quantitative Evaluation Method




[Furukawa and Ponce, CVPR 2008]

# A Detailed View of A Selected Patch



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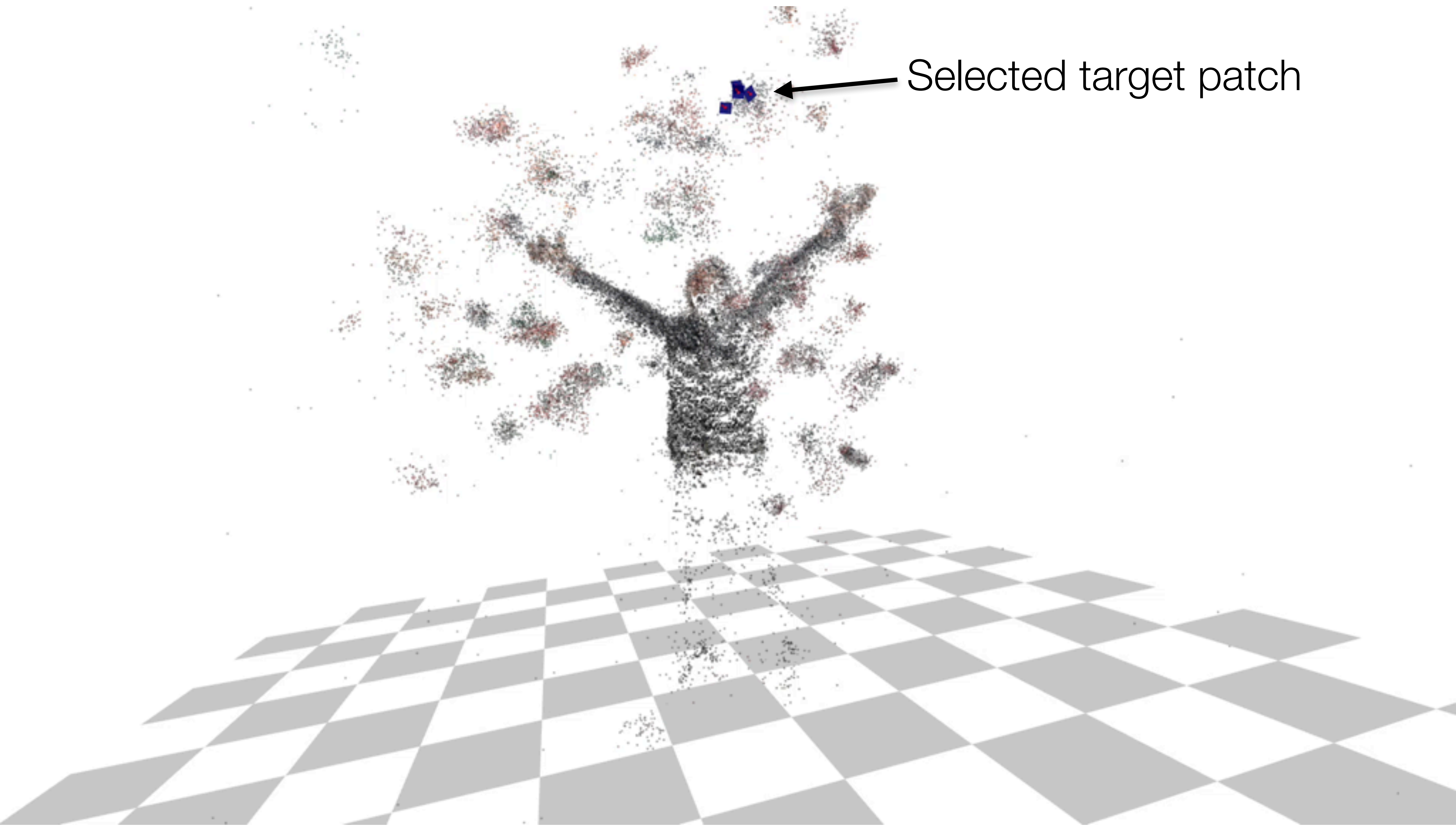

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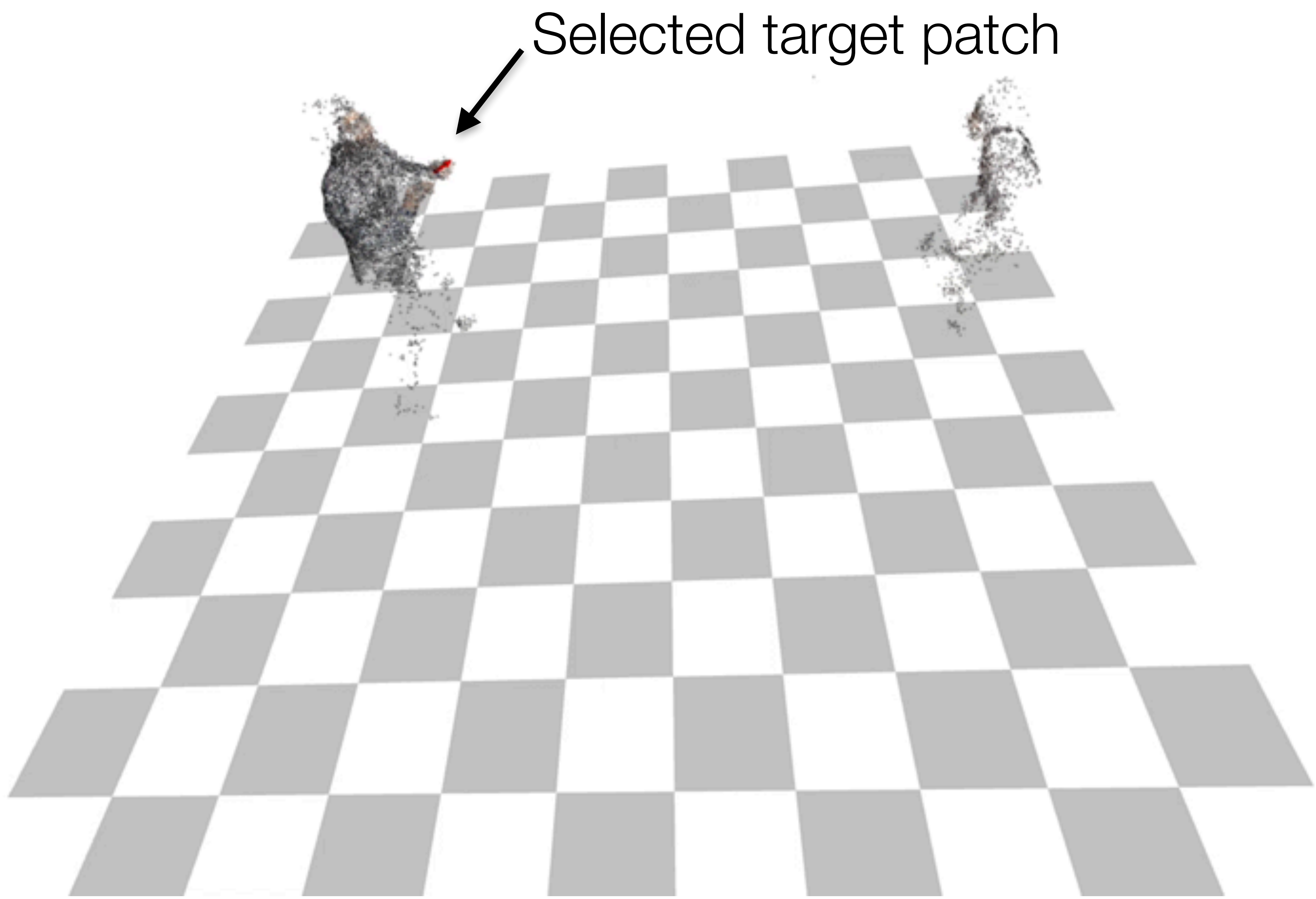

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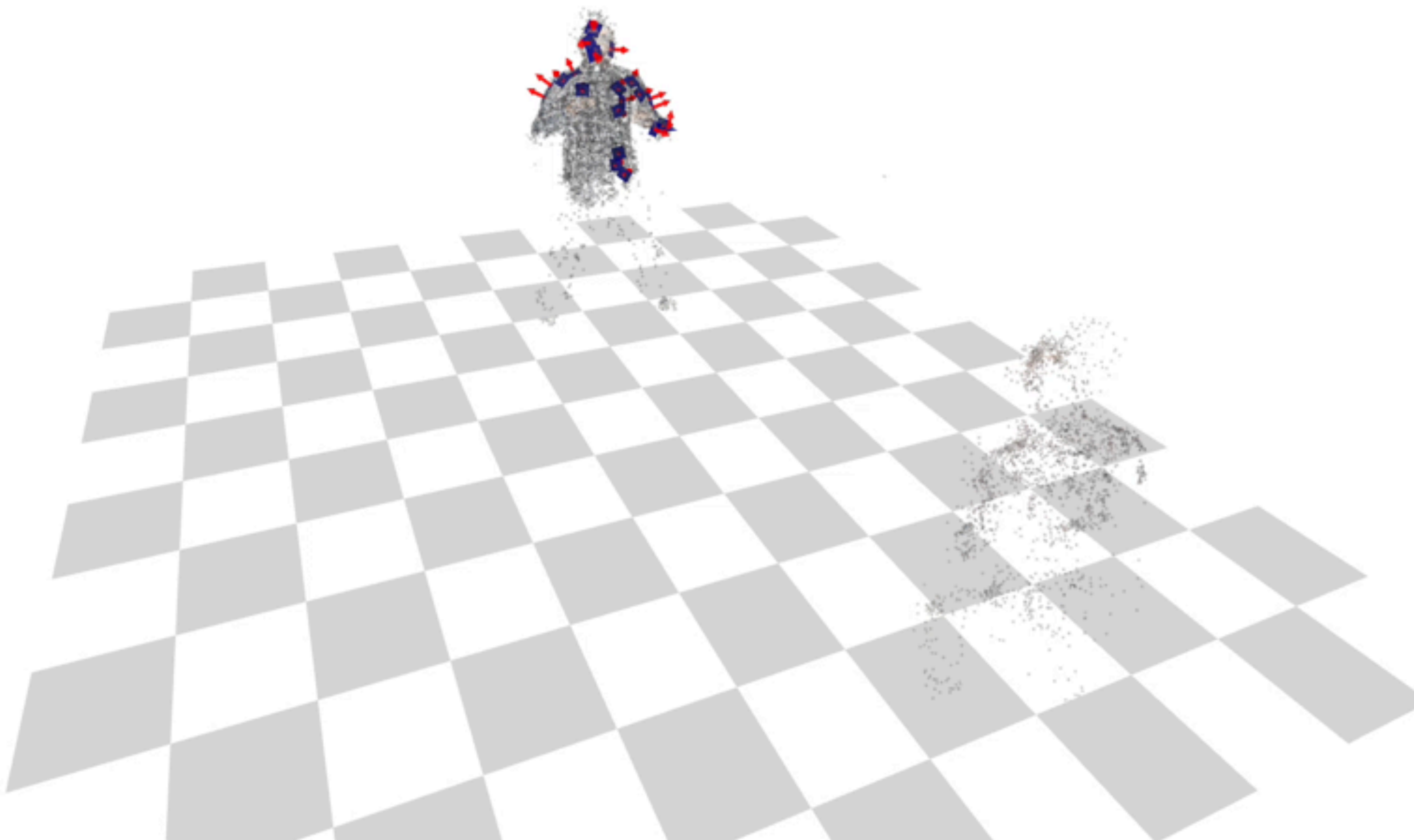

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