Towards Vision Based Robots for Monitoring Built Environments

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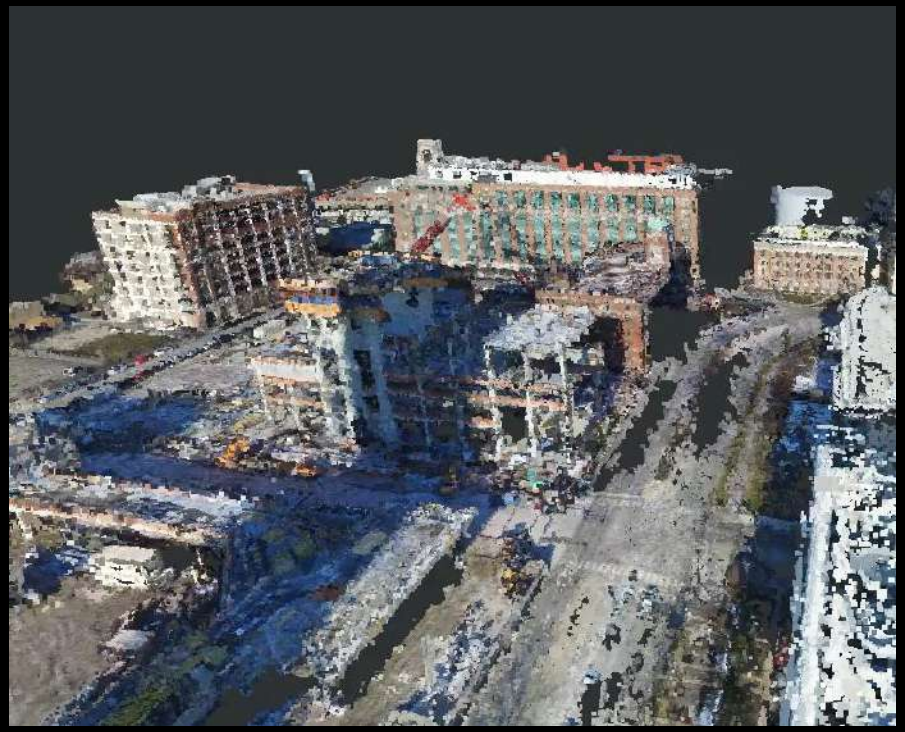
PhD Defense

University of Illinois Urbana-Champaign

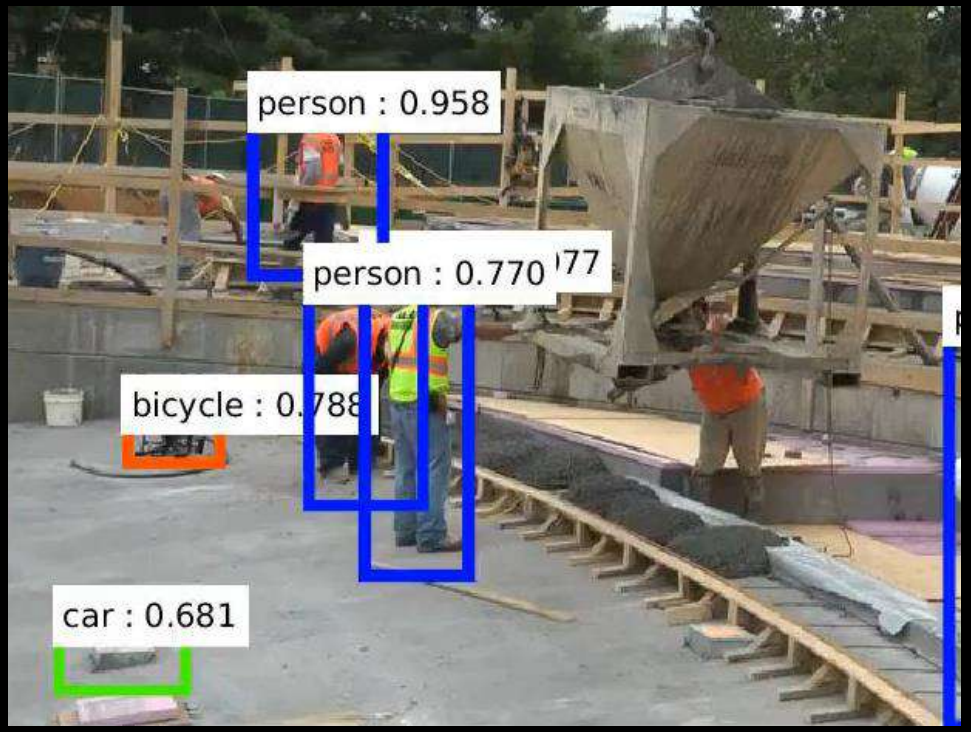
Vision Based Robots Monitoring Built Environments

Vision Based Robots Monitoring Built Environments

Vision Based Robots Monitoring Built Environments

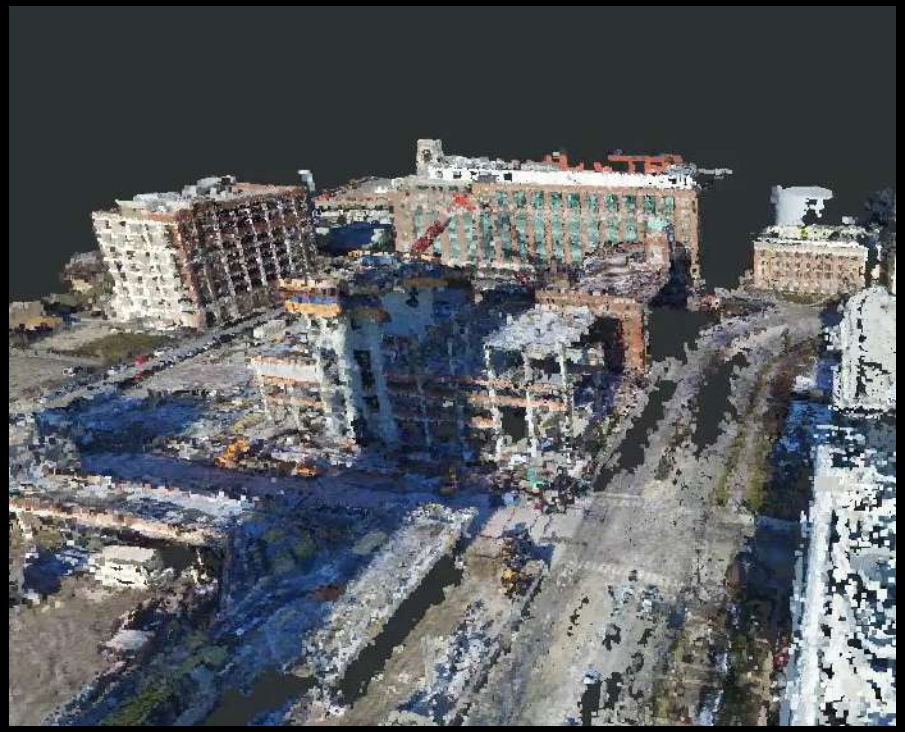


3D Reconstruction to Monitor Progress



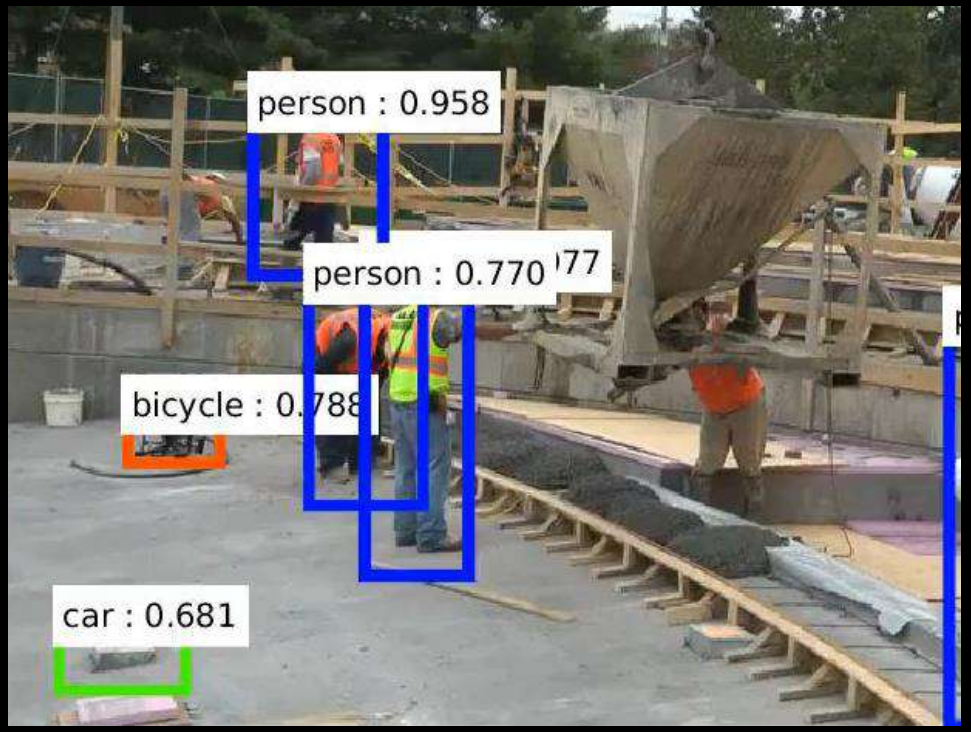
Worker, Equipment, and Material Tracking

Vision Based Robots Monitoring Built Environments



Large projects average 20 month delays and 80% cost overruns

McKinsey & Company (2015)



991 Workers Lost Lives in 2016

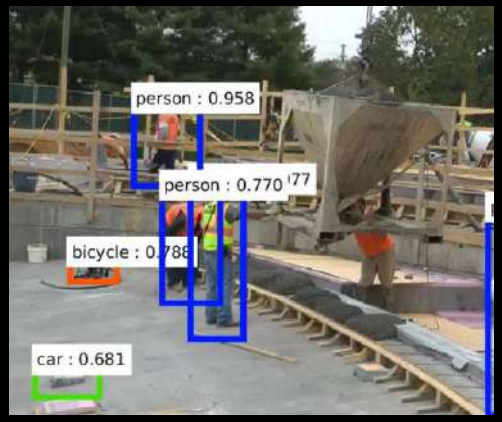
osha.gov/oshstats/commonstats.html

Vision Based Robots Monitoring Built Environments

Data Capture

Mapping

Analysis

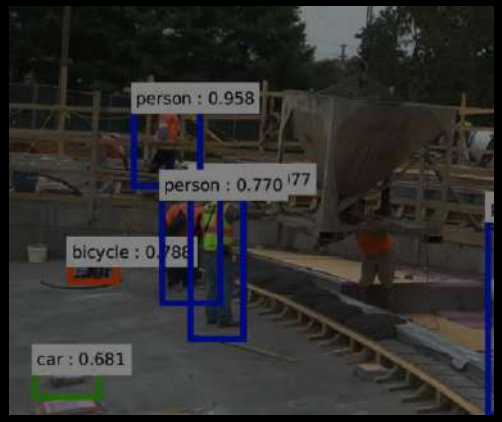


Vision Based Robots Monitoring Built Environments

Data Capture

Mapping

Analysis



Structure from Motion

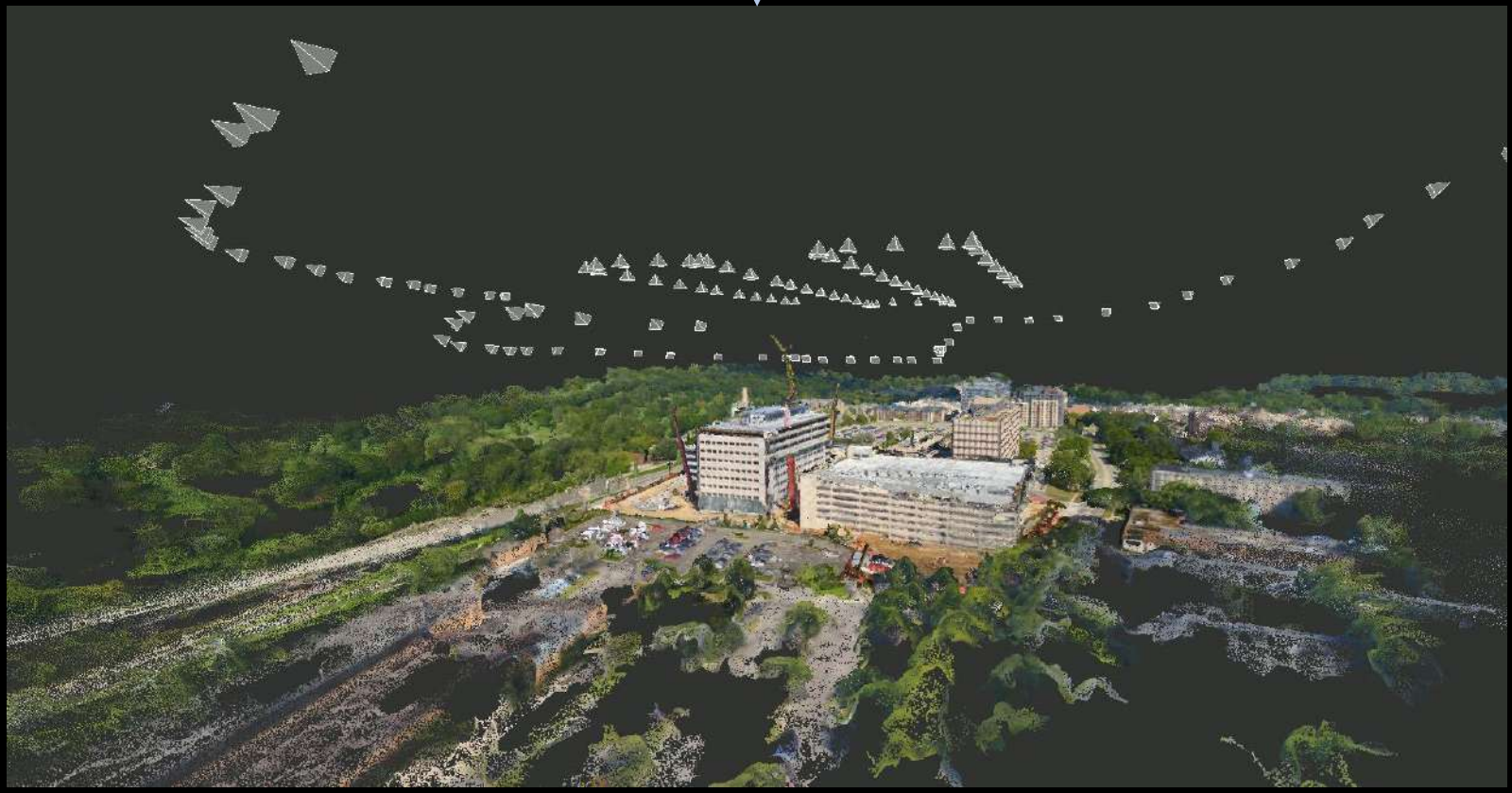
Structure from Motion: From Image Collections

Image Collection

Structure from Motion

Structure from Motion: To 3D Reconstructions

Structure from Motion



3D Reconstruction (Image Locations and 3D Points)

Structure from Motion: And Everything in Between

Images

Detect Features

Matching

Incremental 3D Reconstruction

Poses & Point Cloud

Structure from Motion: And Everything in Between

Images

Detect Features

Matching

Incremental 3D Reconstruction

Poses & Point Cloud

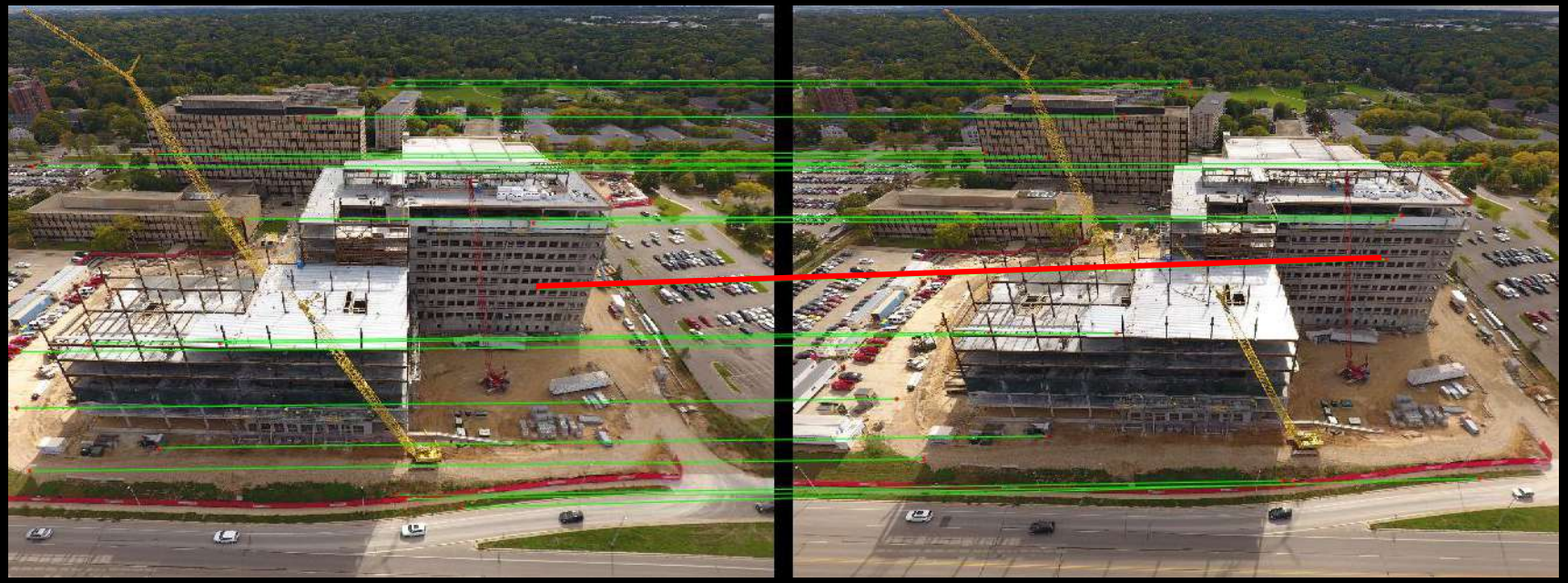
Image Locations with Texture

Structure from Motion: And Everything in Between

Images

Detect Features → **Matching** → Incremental 3D Reconstruction →

Poses & Point Cloud



The SAME location across images

Bad matches happen

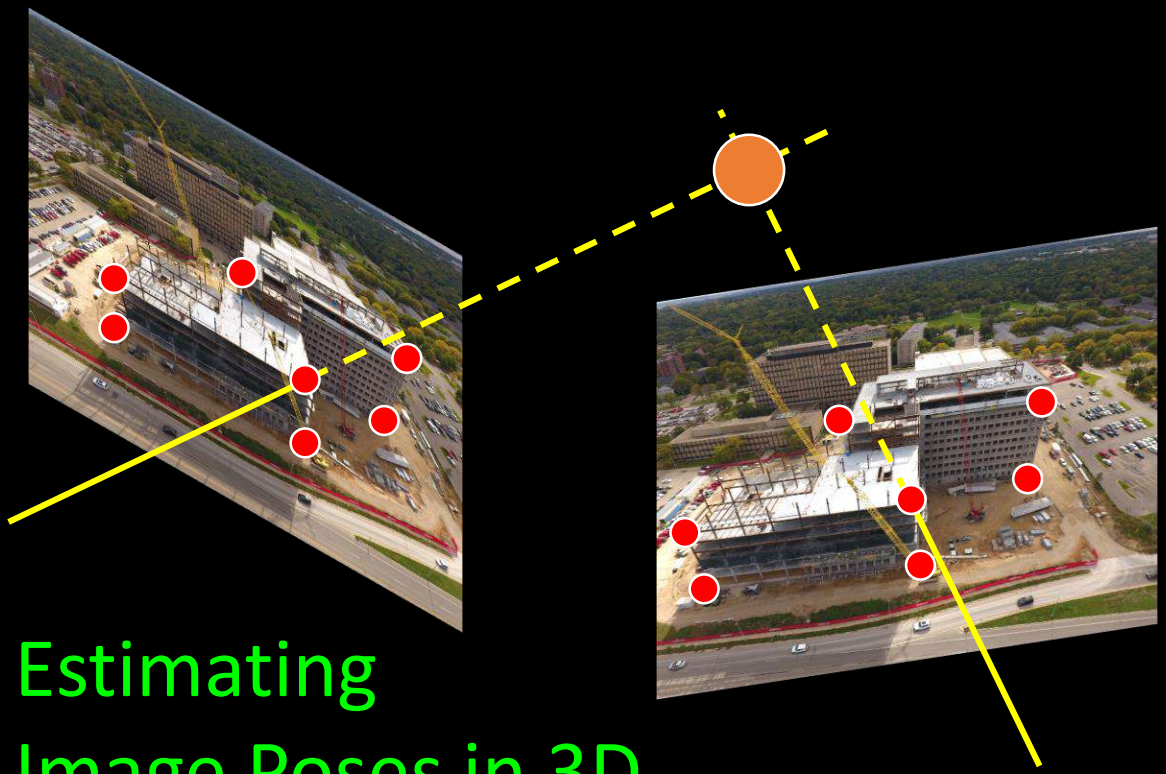
Structure from Motion: And Everything in Between

Images

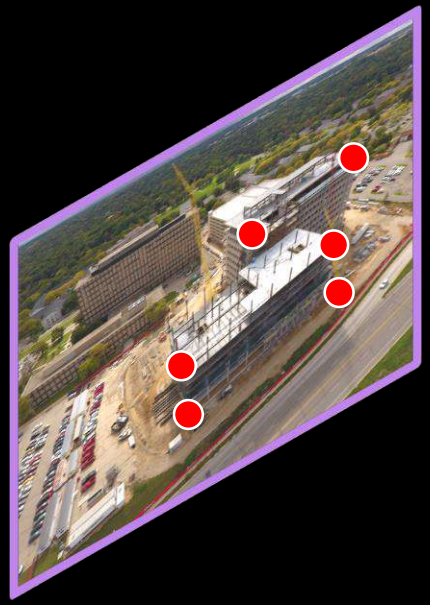
Detect Features → Matching → Incremental 3D Reconstruction

Poses & Point Cloud

Triangulating 3D Point Positions

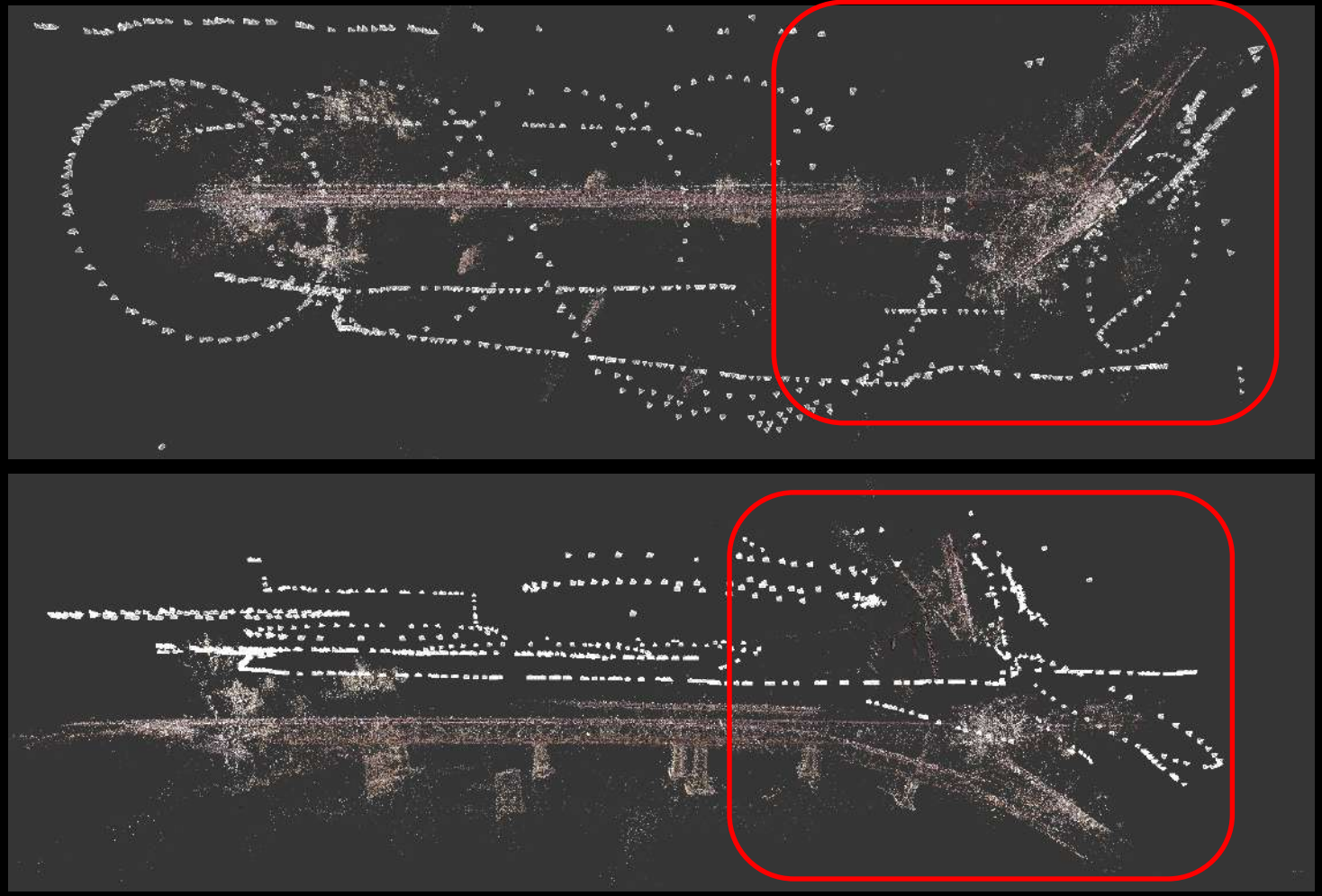


Estimating Image Poses in 3D



Adding new images one at a time

Sometimes Structure from Motion Fails

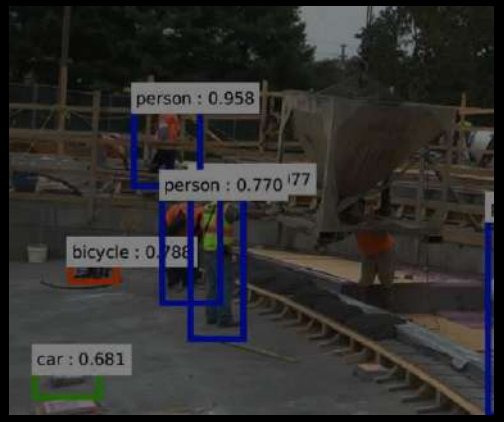


Vision Based Robots Monitoring Built Environments

Data Capture

Mapping

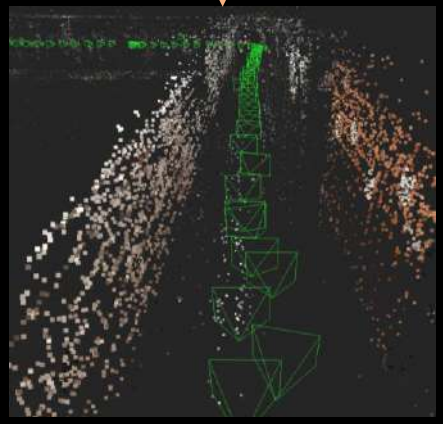
Analysis



Structure from Motion

Overcoming Failures

Simulating Features to Predict Mapping Failure



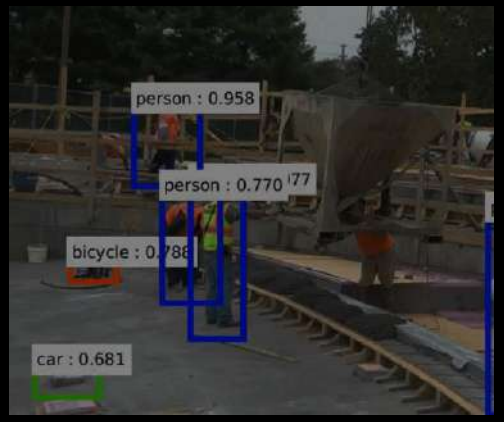
Using Markers for Improved 3D Mapping

Vision Based Robots Monitoring Built Environments

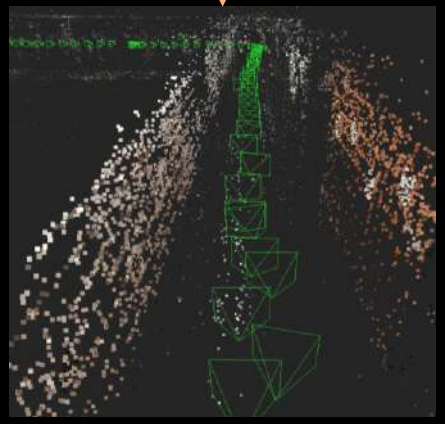
Data Capture

Mapping

Analysis



Structure from Motion



Using Markers for
Improved 3D Mapping

Improved Structure from Motion Using Fiducial Marker Matching

Joseph DeGol,
Timothy Bretl,
Derek Hoiem

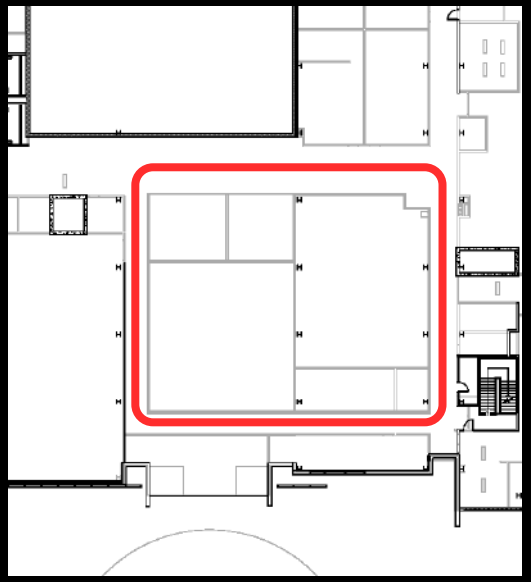
Submitted to ECCV 2018

Introduction

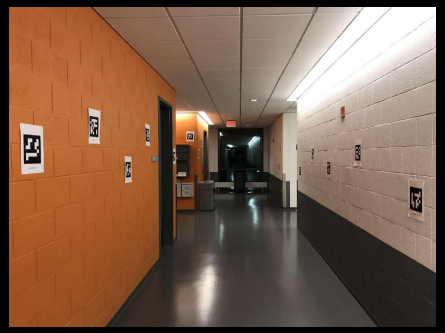
Another Structure from Motion Example

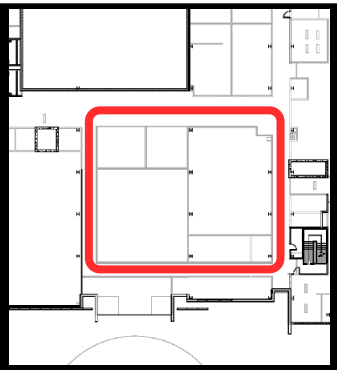
Image Collection

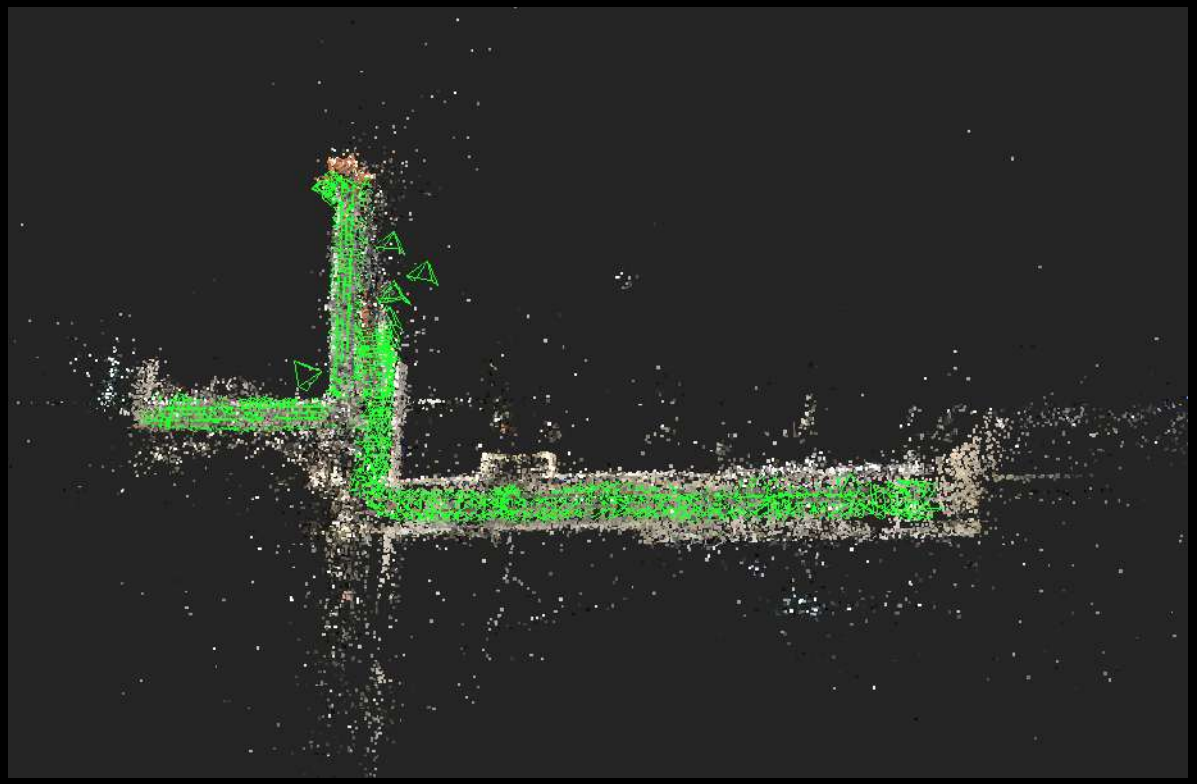
Floor Plan



Structure from Motion Failure



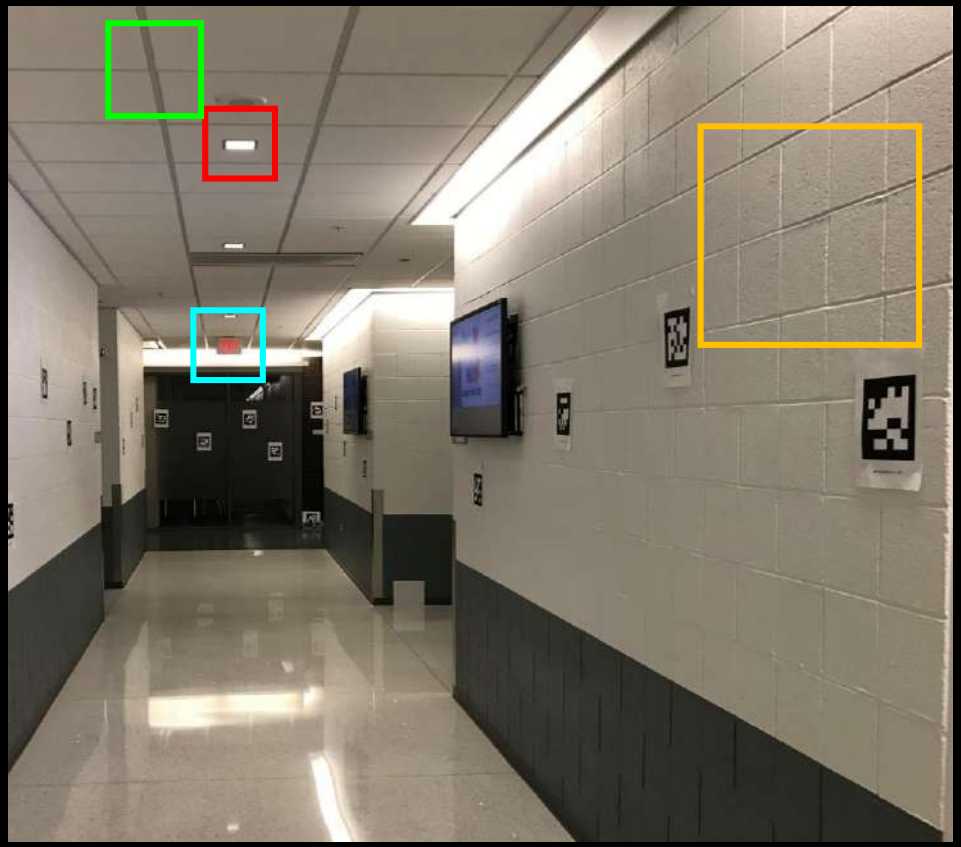


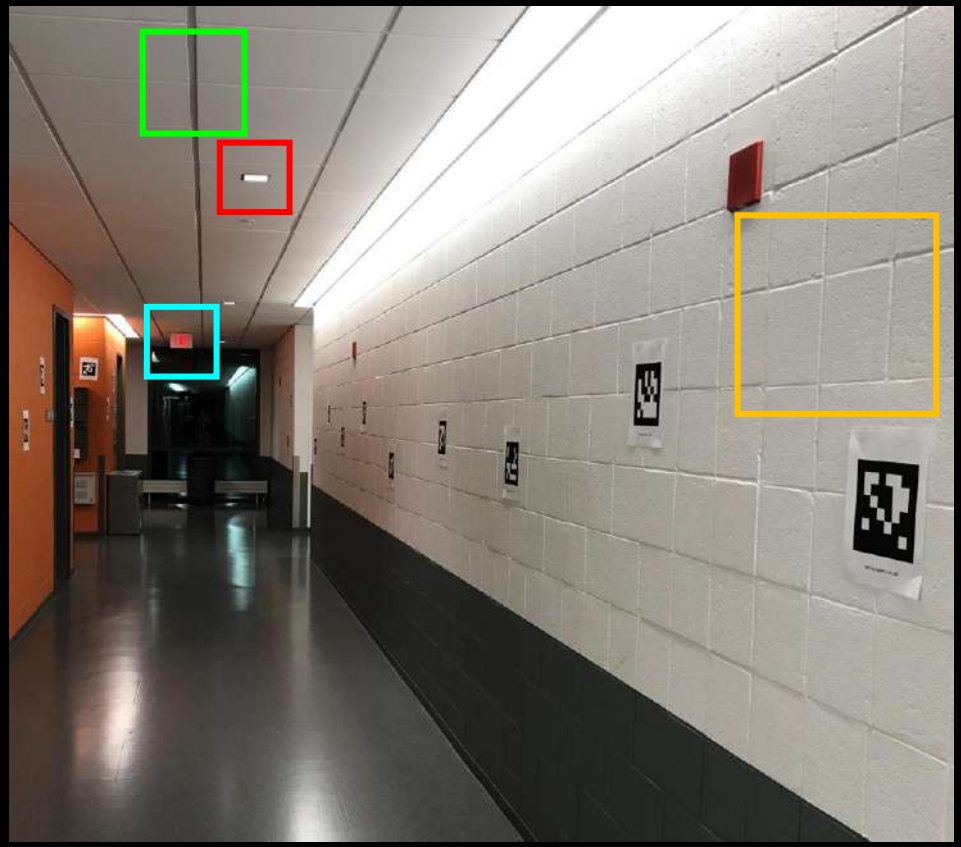


Failed 3D Reconstruction

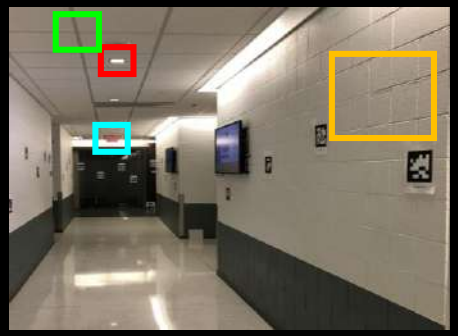
Reasons for Structure from Motion Failures

Repetitive Surfaces: *repetitive features are confused*



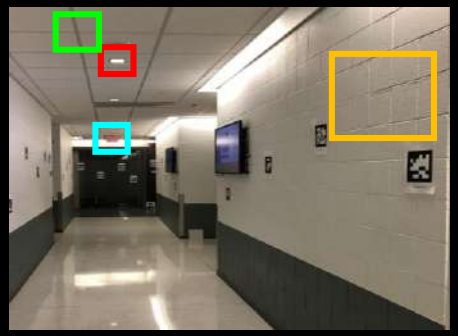


Reasons for Structure from Motion Failures



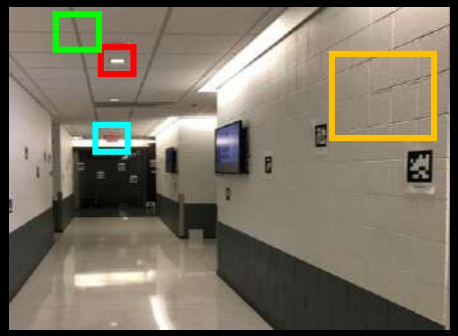
Reflective Surfaces: *reflected feature motion inconsistent with scene motion*

Reasons for Structure from Motion Failures



Textureless Surfaces: *few features to track*

Reasons for Structure from Motion Failures

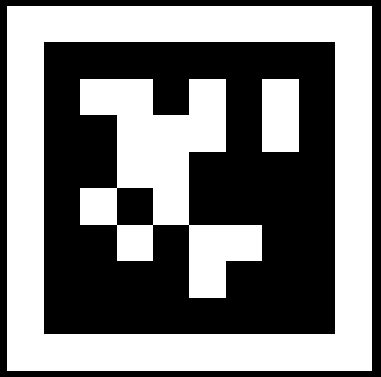


Problem:

Lack of Stable Features

Solution:

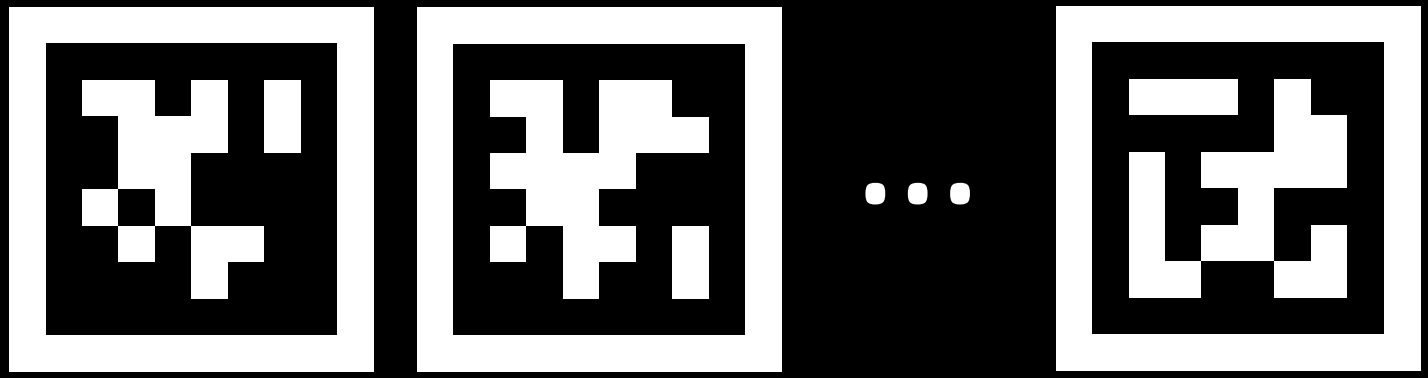
Markers Provide Stable Features



Fiducial Marker Benefits

John Wang and Edwin Olson
AprilTag 2: Efficient and Robust Fiducial Detection

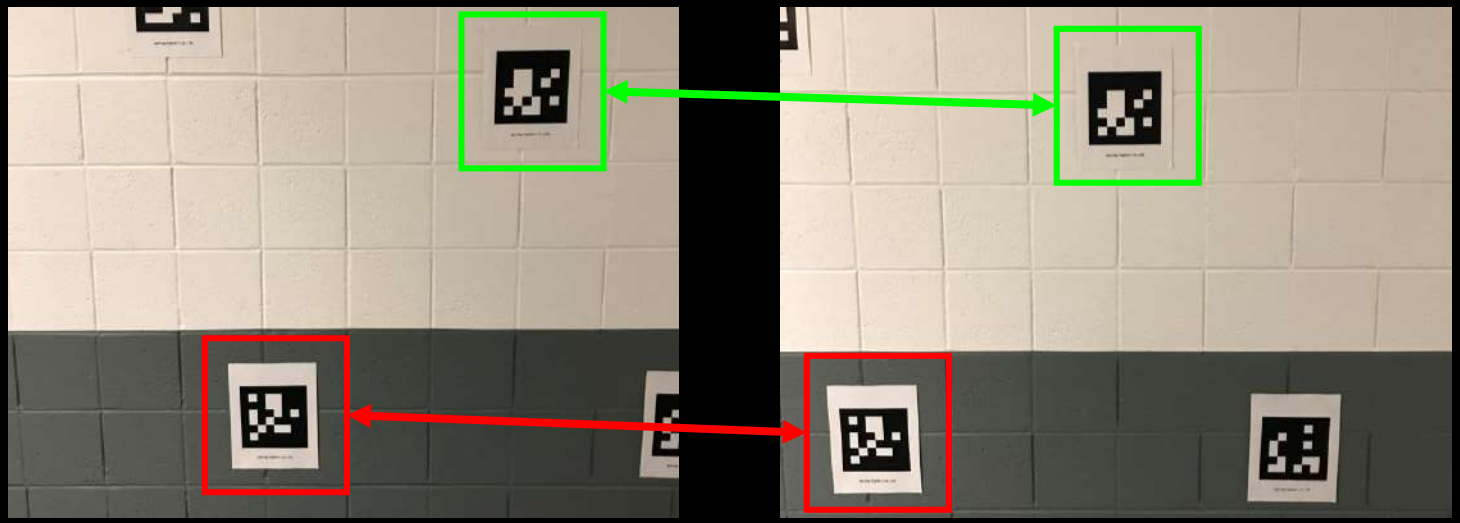
Unique ID



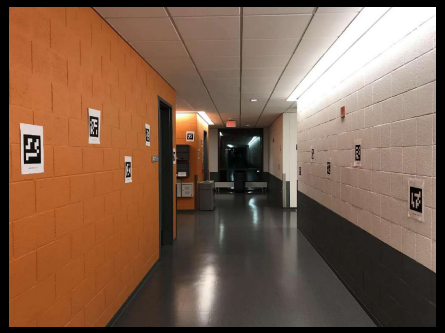
0 1 586

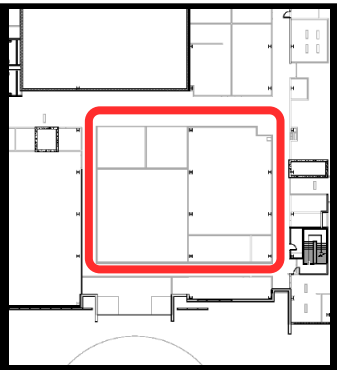
Almost Perfect Matching

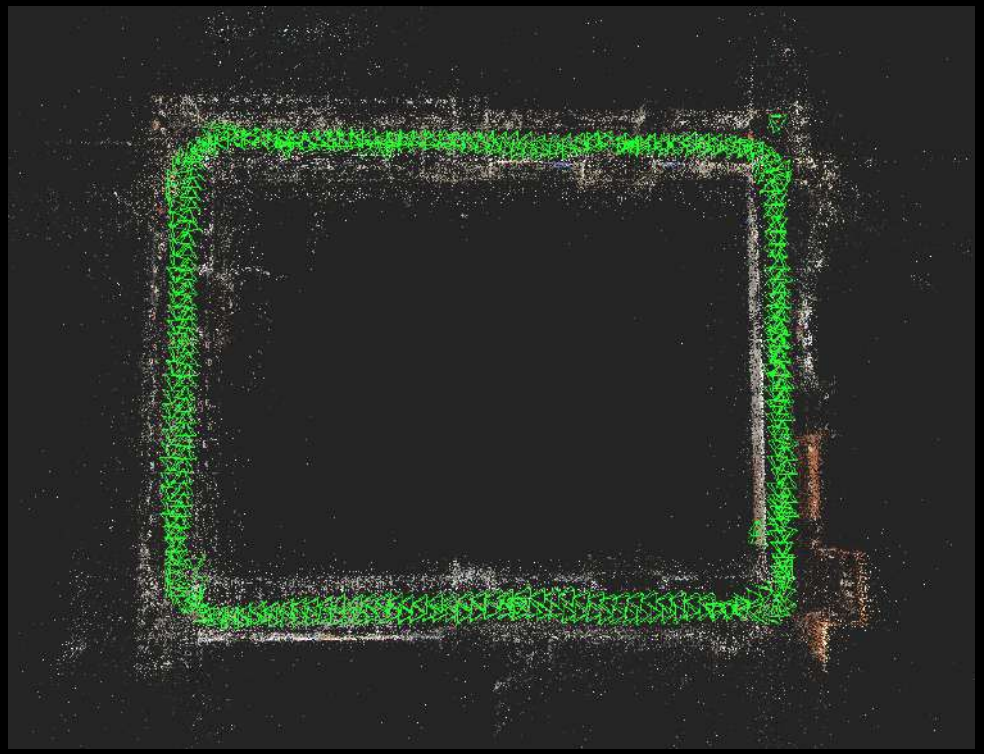
False Positive Rate of 0.000044% [Wang and Olson]



Improved Structure from Motion from Markers







Successful 3D Reconstruction

Improved Structure from Motion Using Fiducial Marker Matching

Using Marker Matches

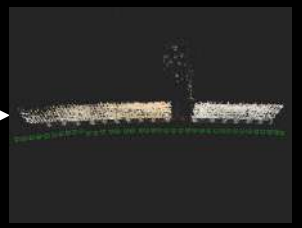
Structure from Motion Pipeline

Images

Detect Features

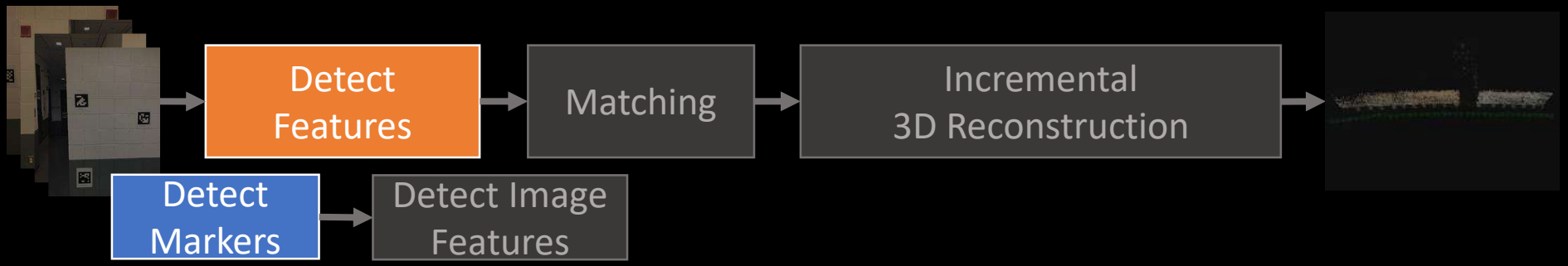
Matching

Incremental 3D Reconstruction

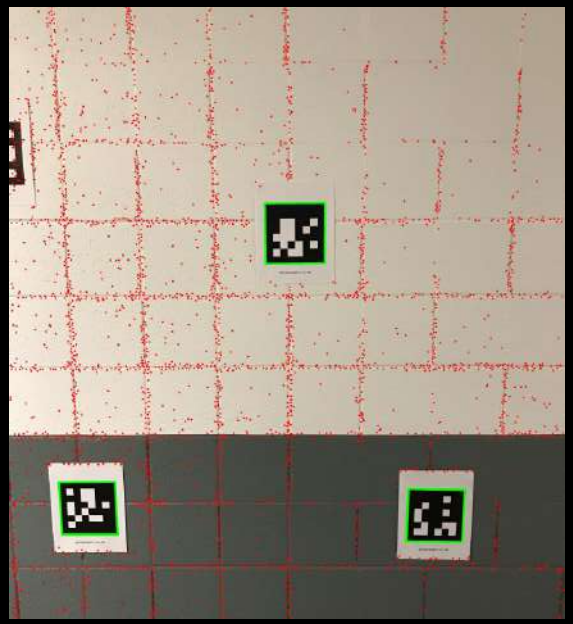


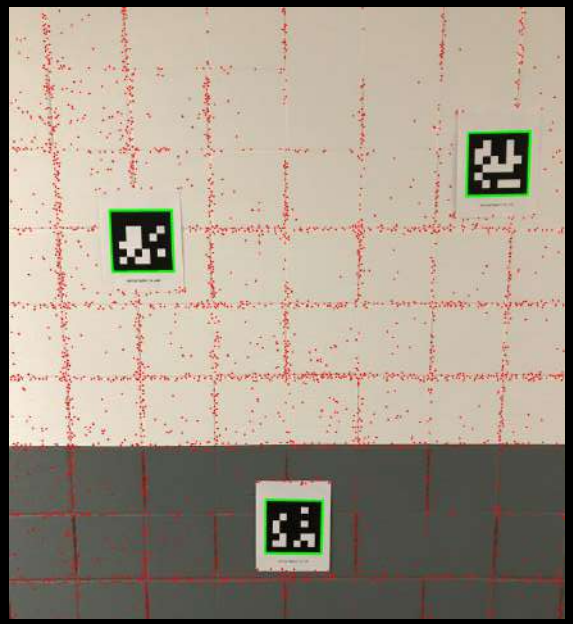
Poses & Point Cloud

Structure from Motion Pipeline



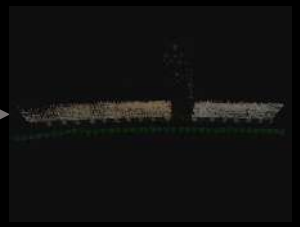
Detect Markers





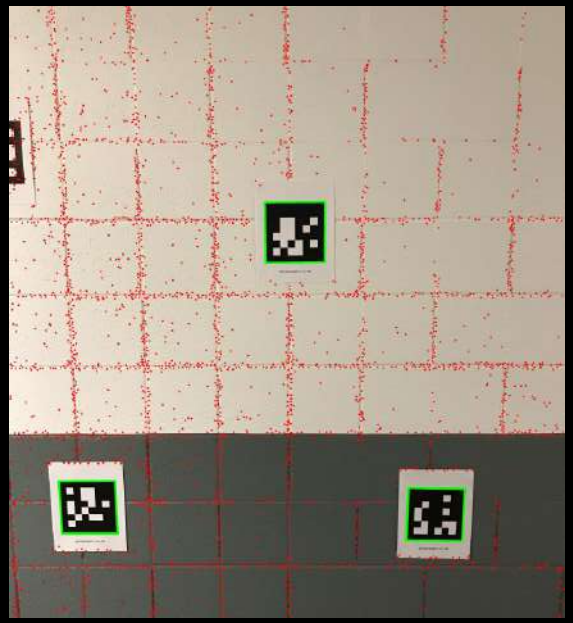
Structure from Motion Pipeline

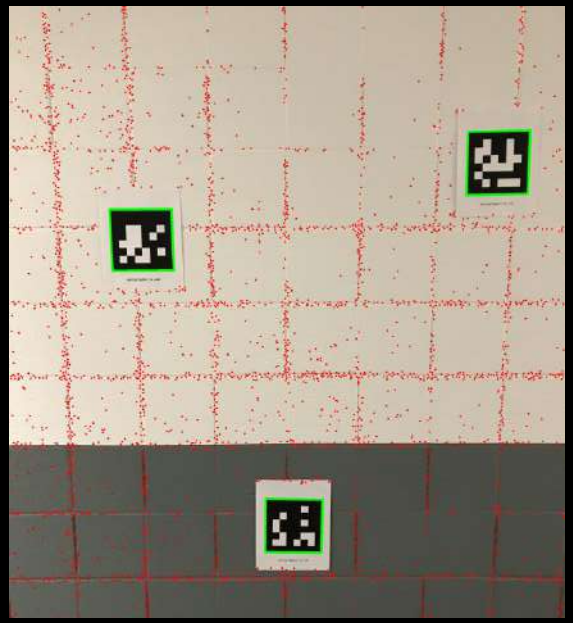
Detect Features → Matching → Incremental 3D Reconstruction



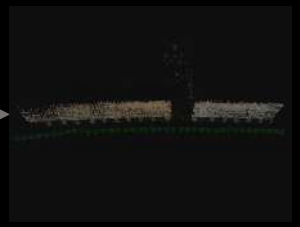
Detect Markers → Detect Image Features

Detect Image Features



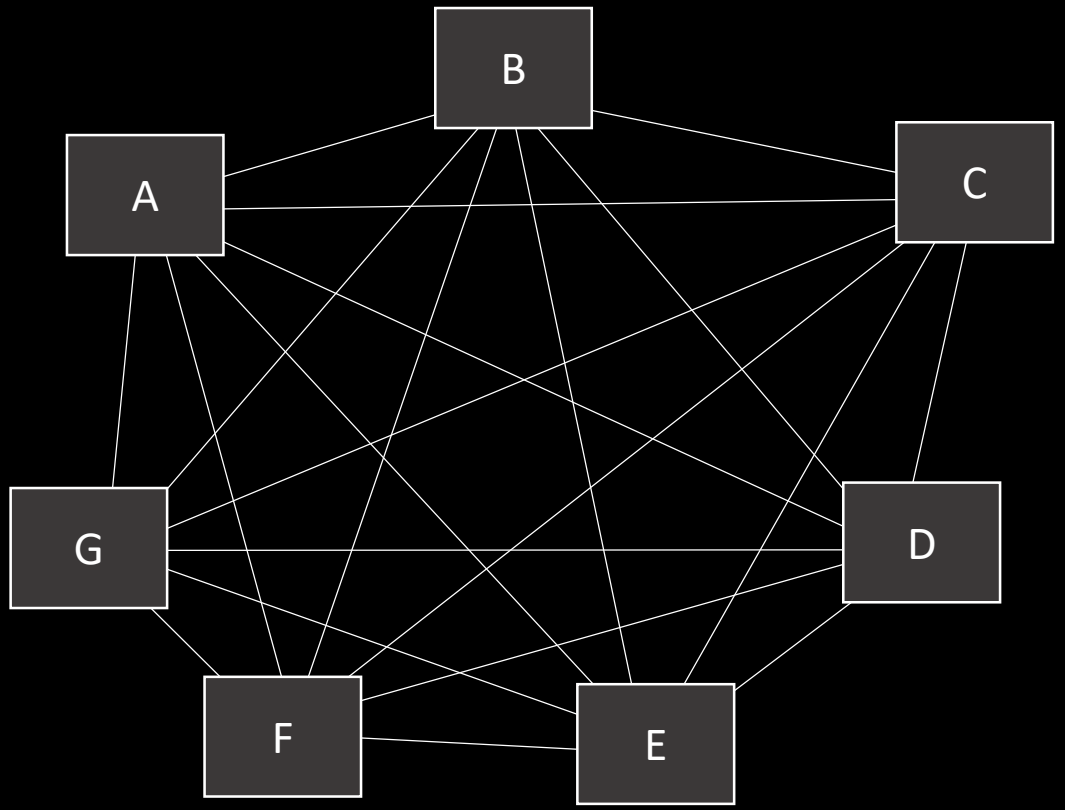


Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction → 

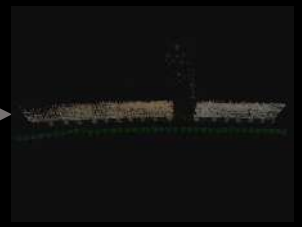
Candidate Pairs → Image Matching

21 possible image pairs



Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction



Candidate Pairs → Image Matching

A

B

C

Possible bad matches

G

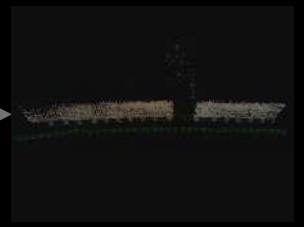
D

F

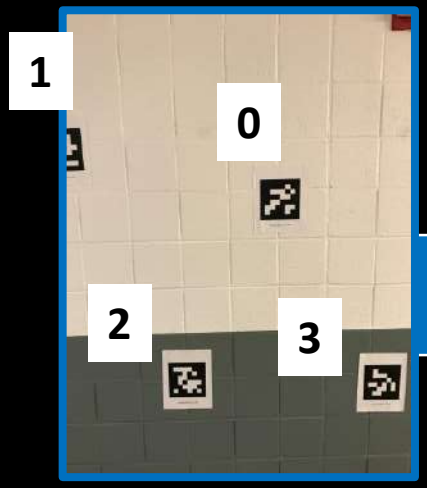
E

Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction



Candidate Pairs → Image Matching

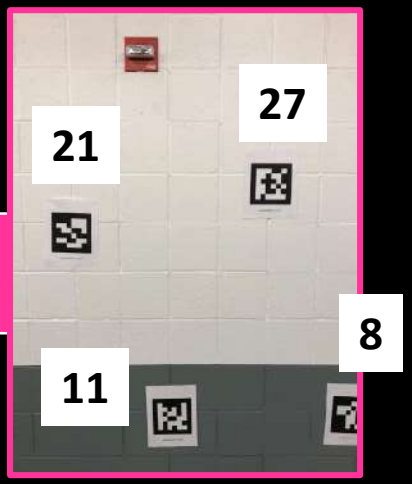


A

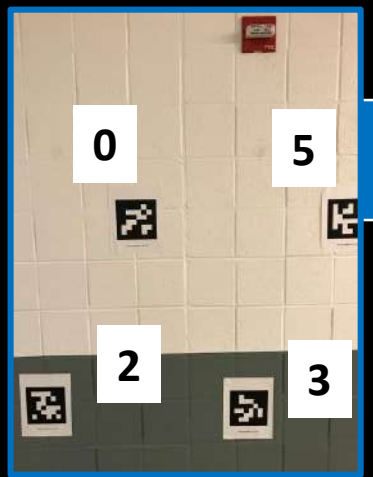
B

Edges Removed for 0 matches

C



3 matches



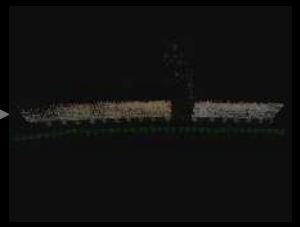
G

D

F

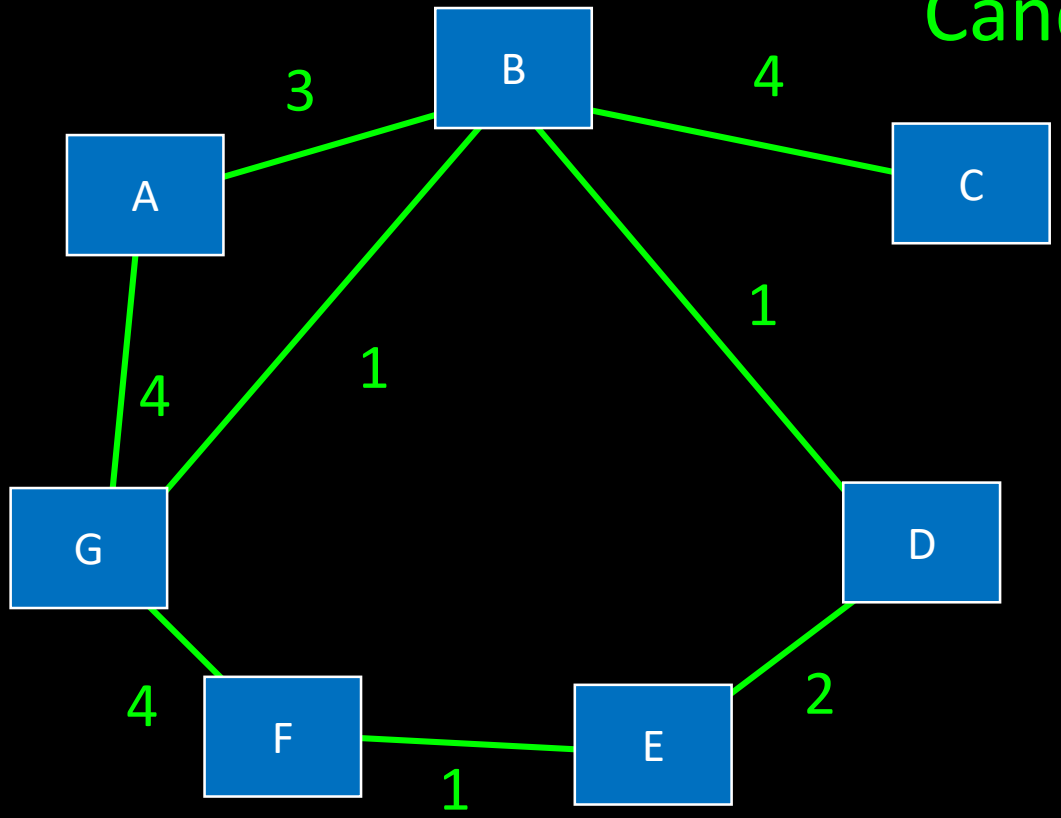
E

Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction → 

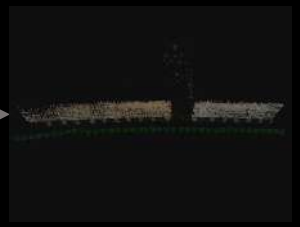
Candidate Pairs → Image Matching

8 Remaining Candidate Pairs



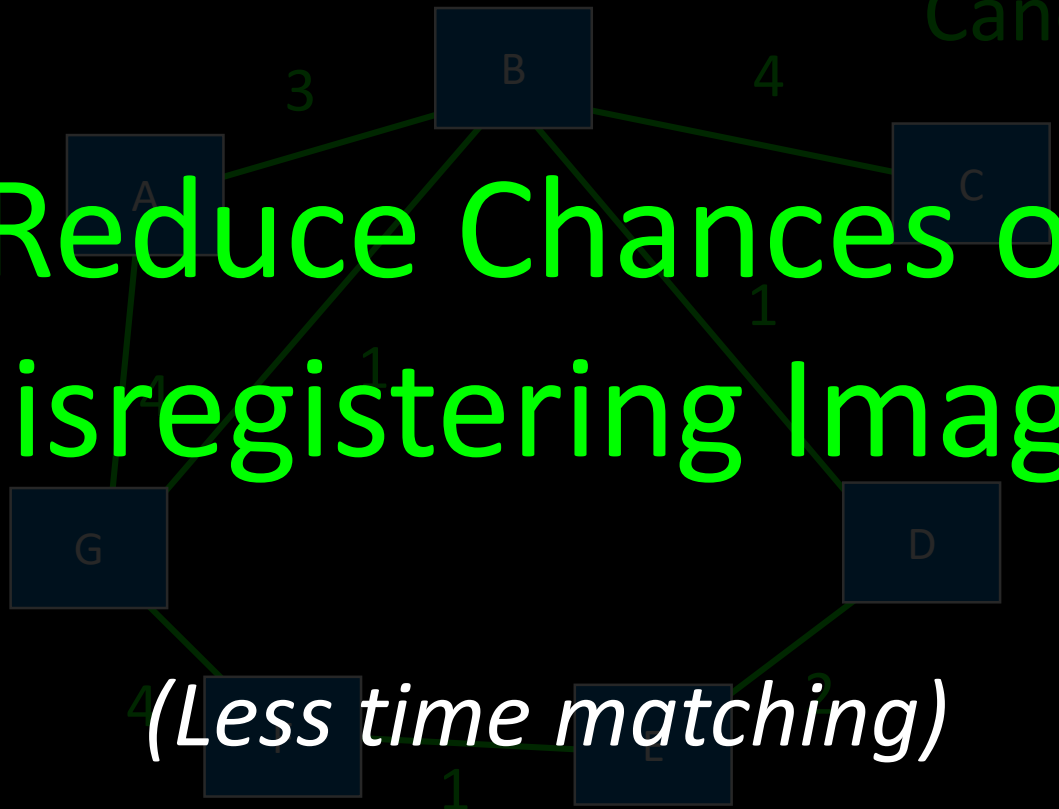
Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction



Candidate Pairs → Image Matching

8 Remaining Candidate Pairs

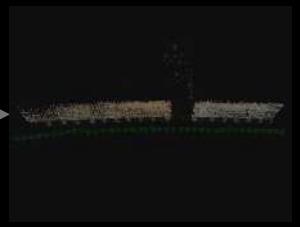


Reduce Chances of Misregistering Images

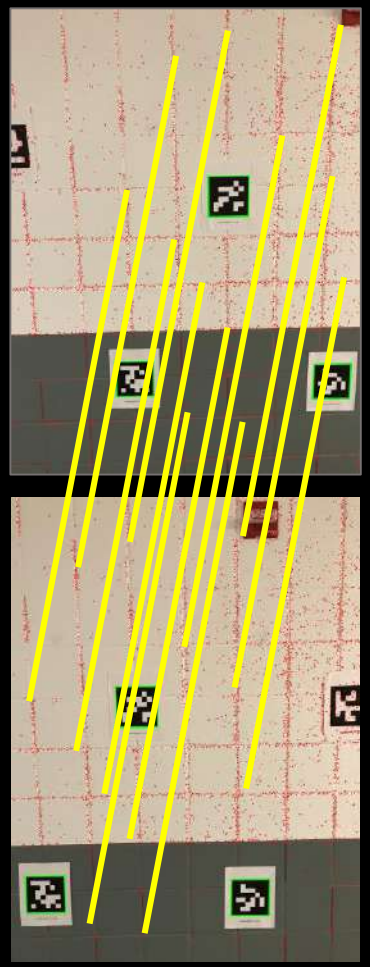
(Less time matching)

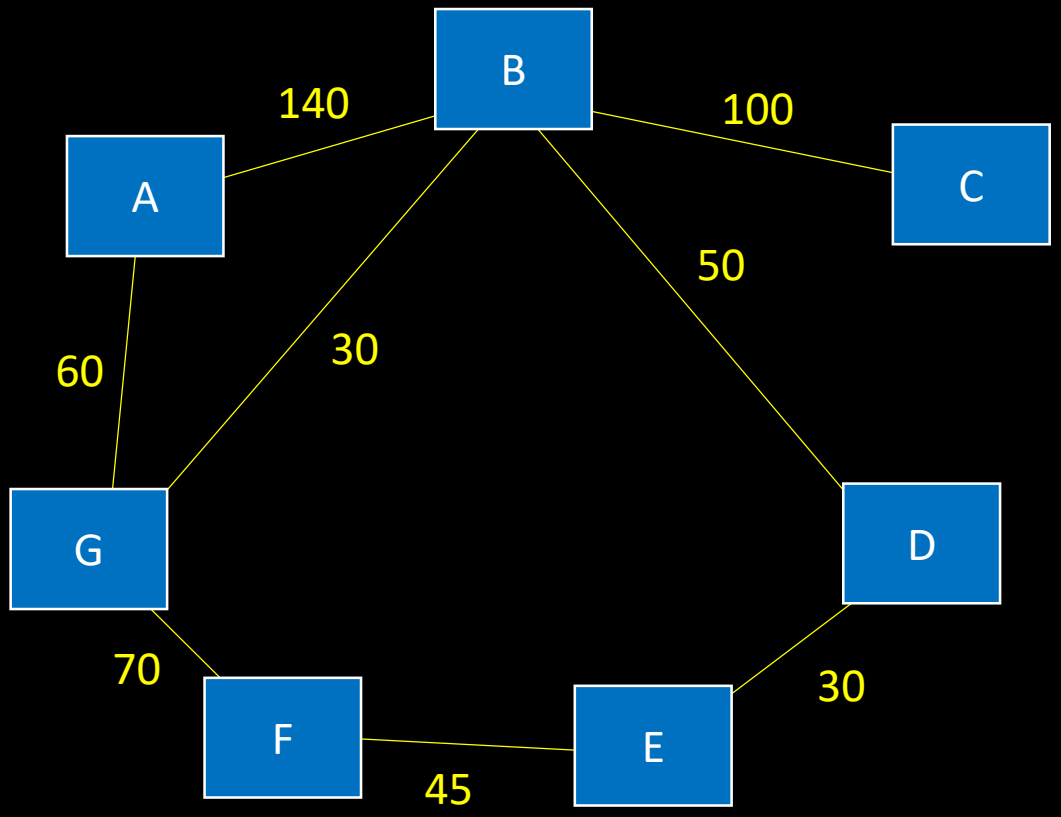
Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction

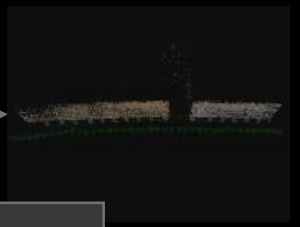


Candidate Pairs → Image Matching



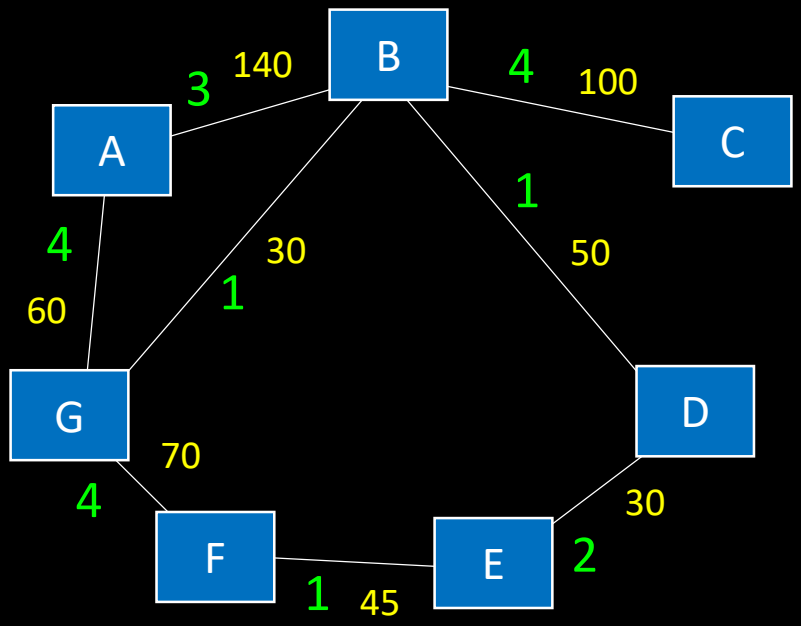


Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph



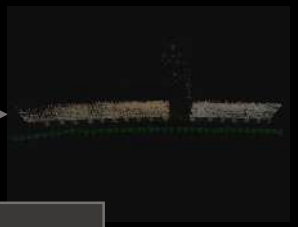
Marker Matches

Image Feature Matches

3D Reconstruction

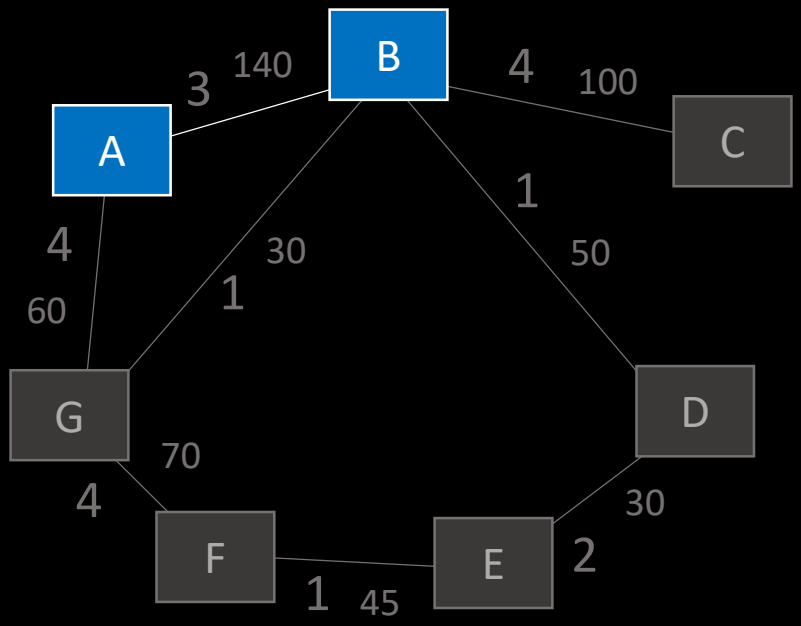
Need to start the reconstruction…

Structure from Motion Pipeline

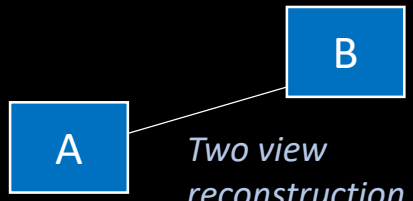
Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph

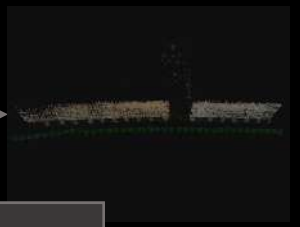


3D Reconstruction



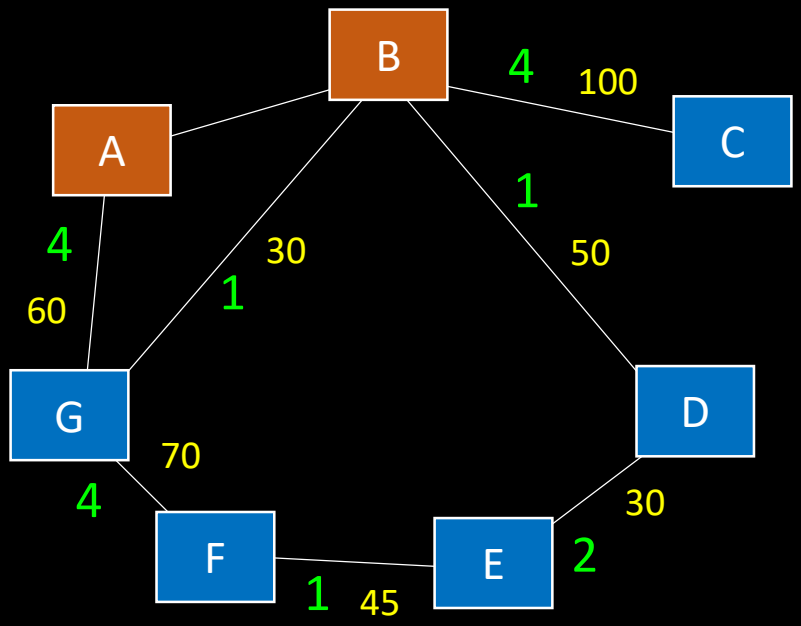
Two view reconstruction

Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph

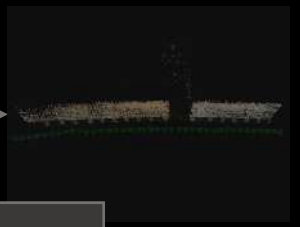


3D Reconstruction

AB

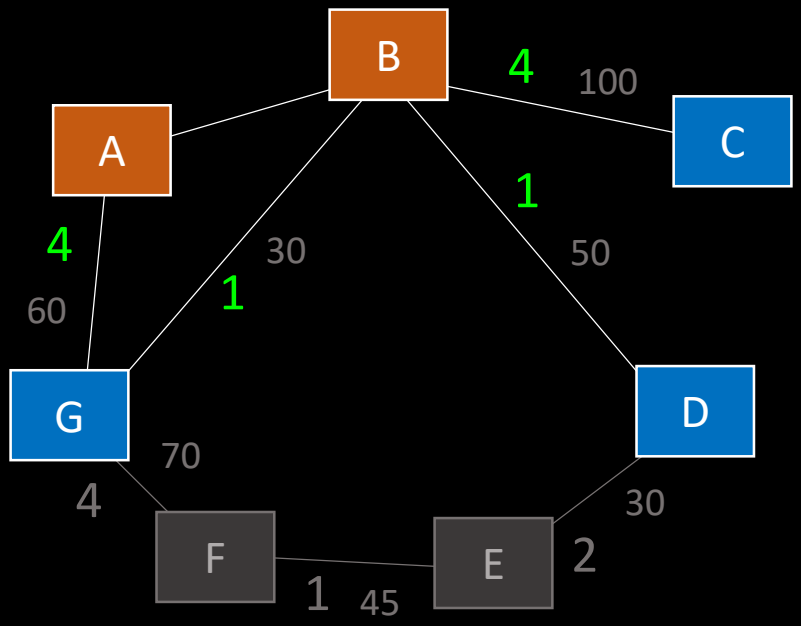
Need to add images to the reconstruction…

Structure from Motion Pipeline

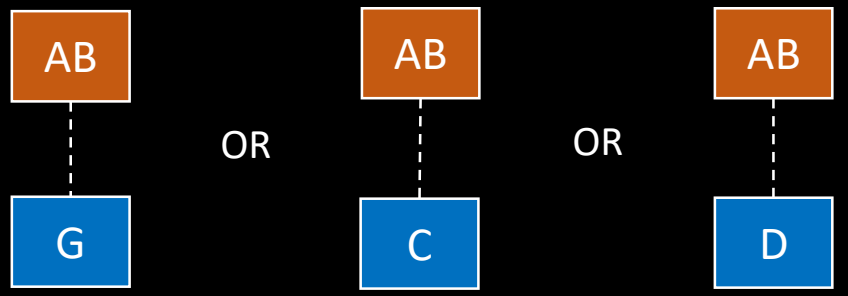
Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph



3D Reconstruction



5 marker matches

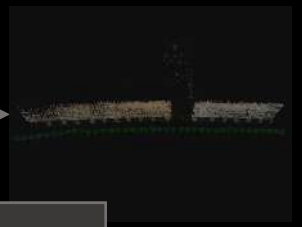
4 marker matches

1 marker match

Rule 1: More Marker Matches Wins

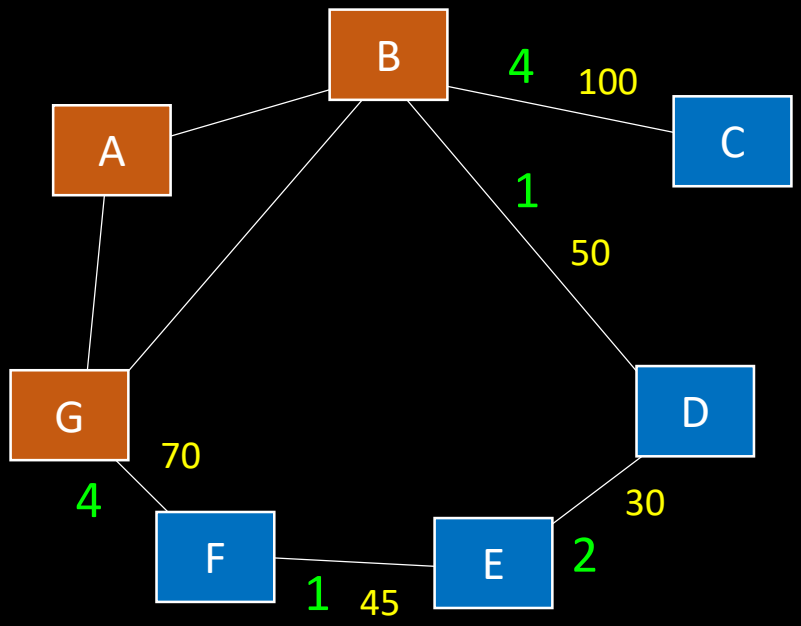
Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction



2 View Recon ⇢ Resection ⇄ BA

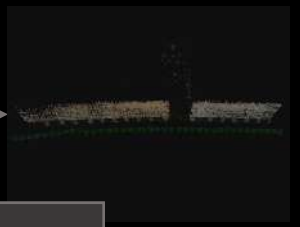
Match Graph



3D Reconstruction

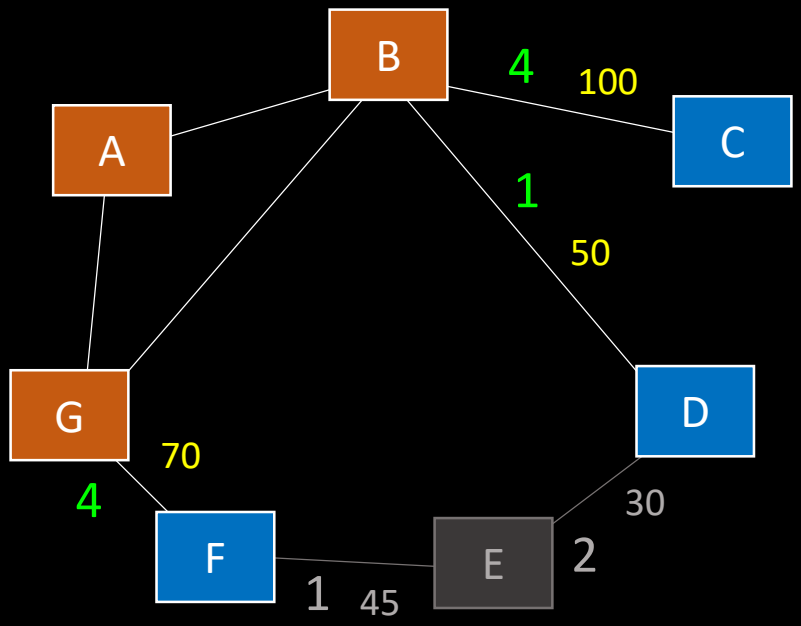
ABG

Structure from Motion Pipeline

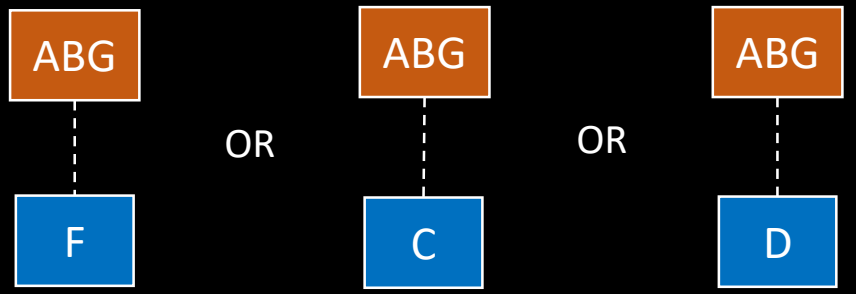
Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph



3D Reconstruction



4 marker matches

70 image matches

OR

4 marker matches

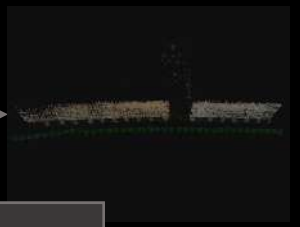
100 image matches

OR

1 marker match

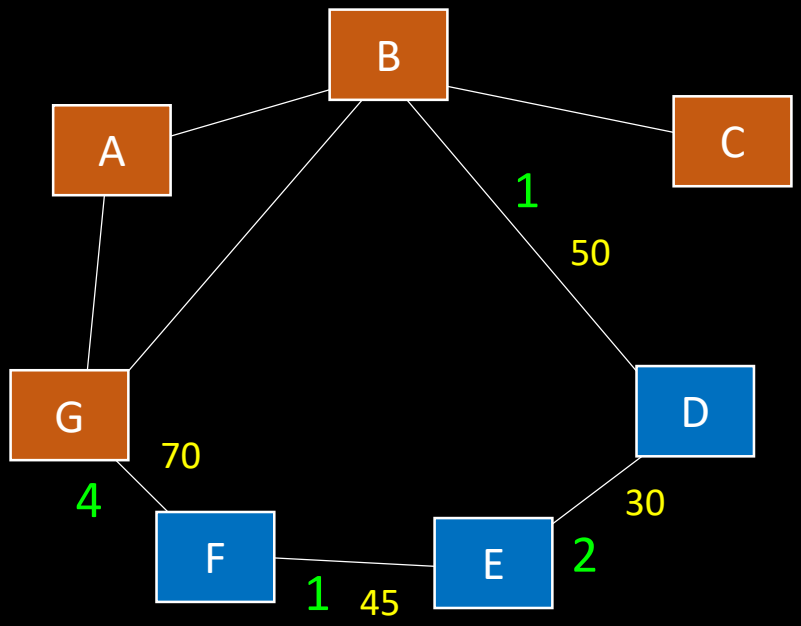
Rule 2: Feature Matches Break Ties

Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph

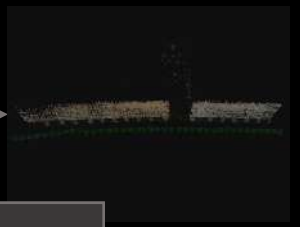


3D Reconstruction

ABGC

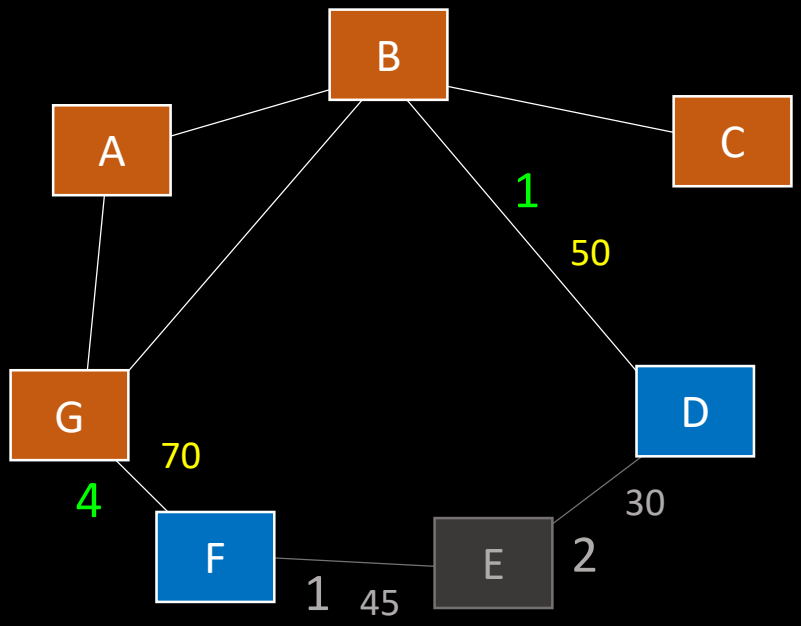
Continue this process to resection all images…

Structure from Motion Pipeline

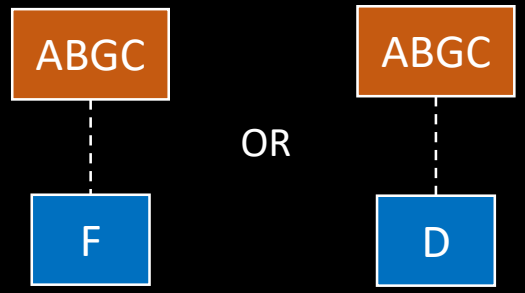
Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon → Resection → BA

Match Graph



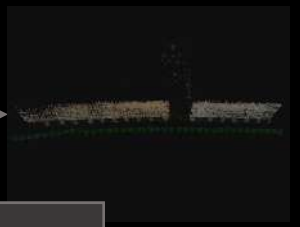
3D Reconstruction



4 marker matches

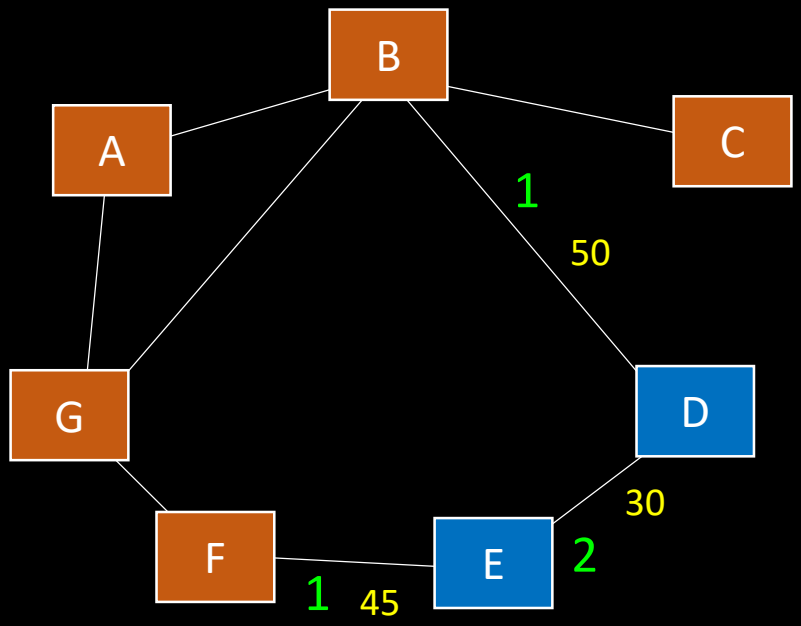
1 marker match

Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

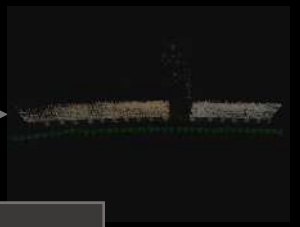
Match Graph



3D Reconstruction

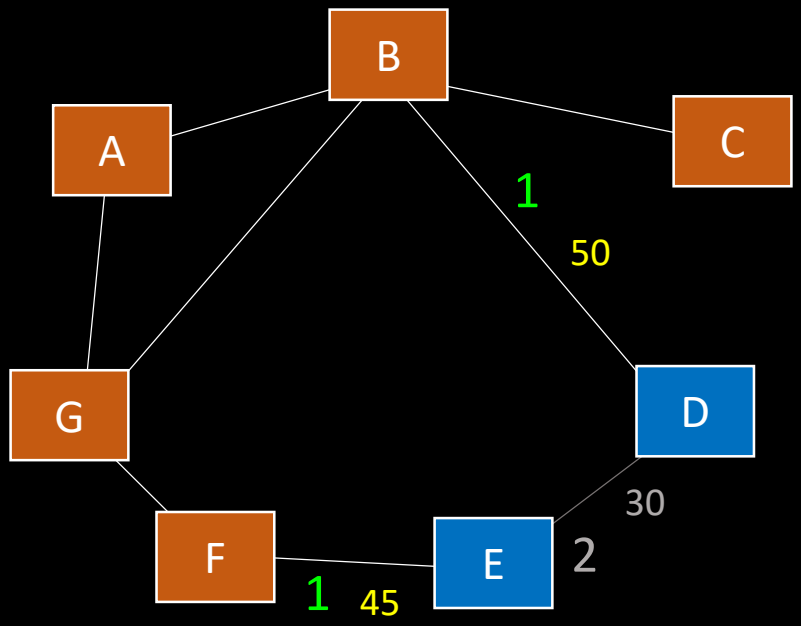
ABGCF

Structure from Motion Pipeline

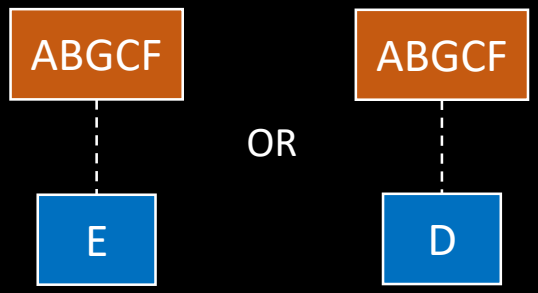
Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph



3D Reconstruction



1 marker match

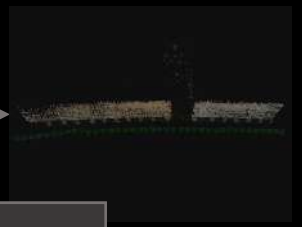
45 image matches

OR

1 marker match

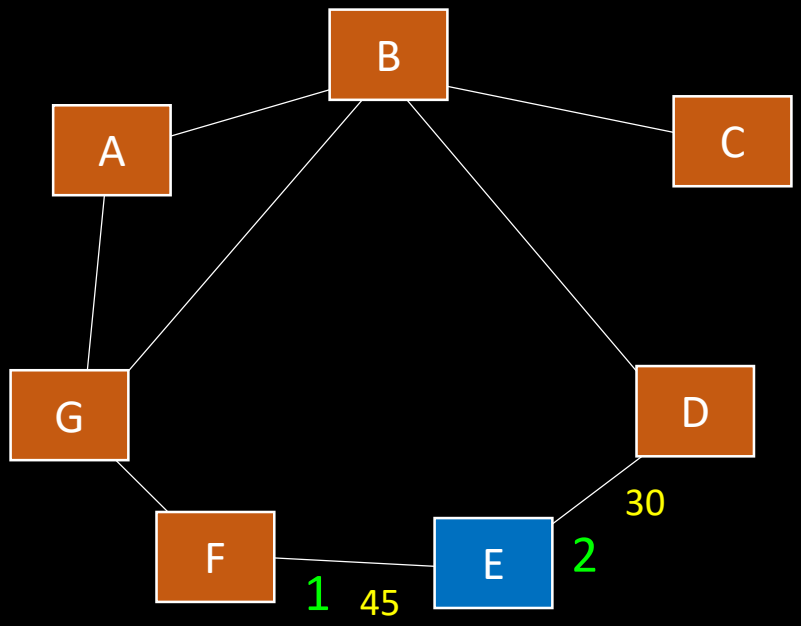
50 image matches

Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction → 

2 View Recon ⇢ Resection ⇄ BA

Match Graph

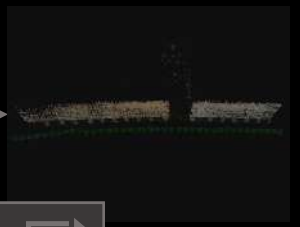


3D Reconstruction

ABGCFD

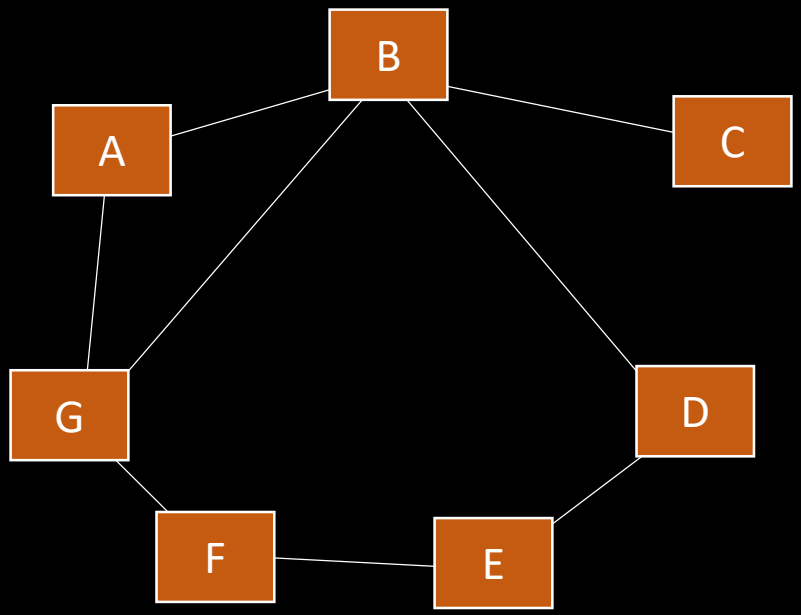
Structure from Motion Pipeline

Detect Features → Matching → Incremental 3D Reconstruction



2 View Recon ⇢ Resection ⇄ BA

Match Graph



3D Reconstruction

ABGCFDE

Improved Structure from Motion Using Fiducial Marker Matching

Data and Results

Experimental Setup

Dataset

- 16 Indoor image collections *(3530 total images)*
- Tens of AprilTags used in smaller scenes
- Hundreds of AprilTags used in larger scenes
- 3 Buildings

ECEB

Newmark

MUF @ Research Park

Experimental Setup

Dataset

- 16 Indoor image collections *(3530 total images)*
- Tens of AprilTags used in smaller scenes
- Hundreds of AprilTags used in larger scenes
- 3 Buildings

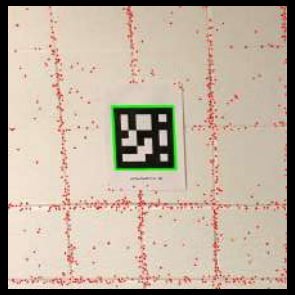
ECEB

Newmark

MUF @ Research Park

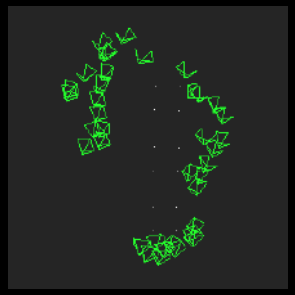
Methods for Comparison

OpenSfM
by Mappilary



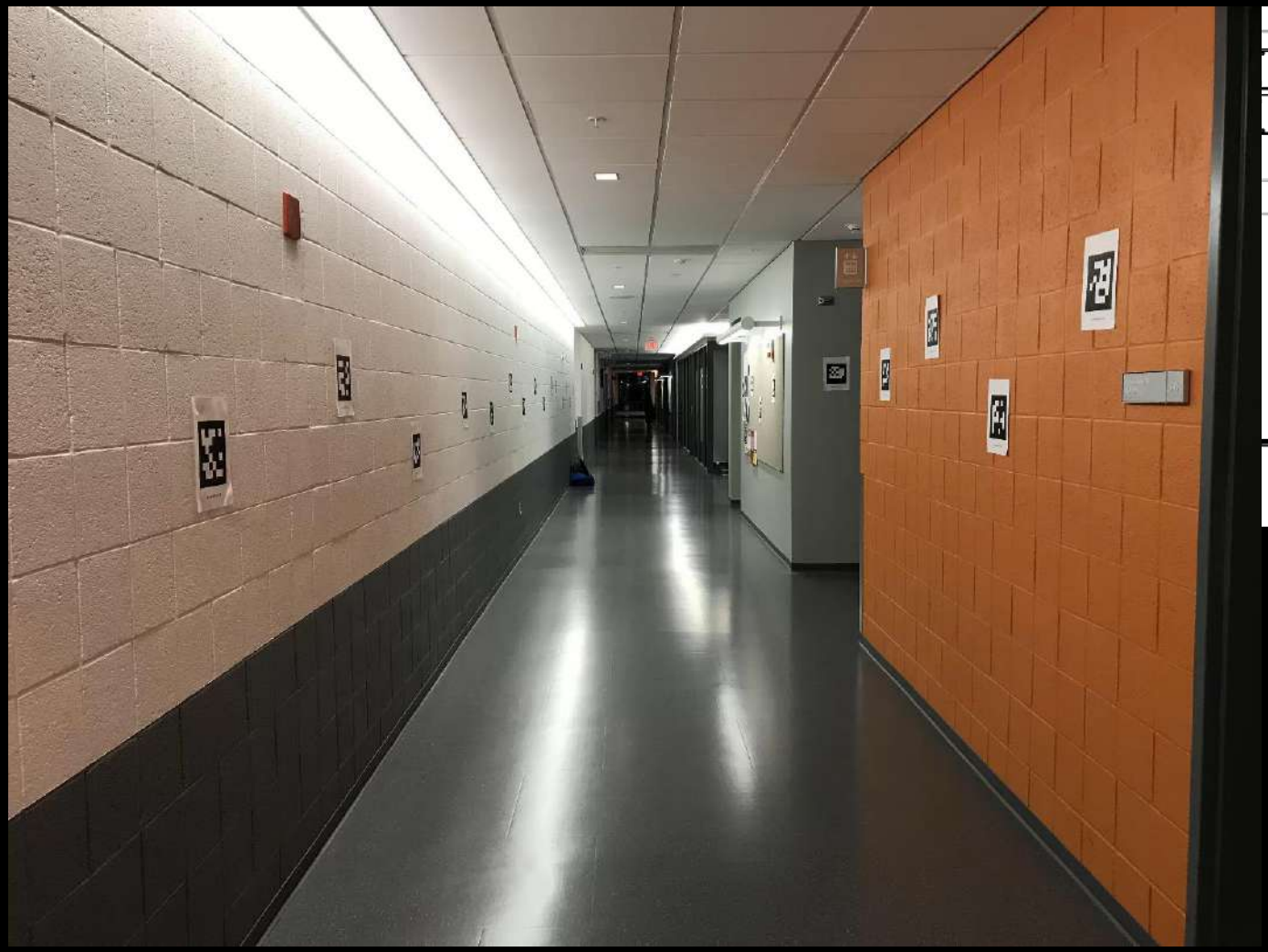
OpenSfM
+ Masking

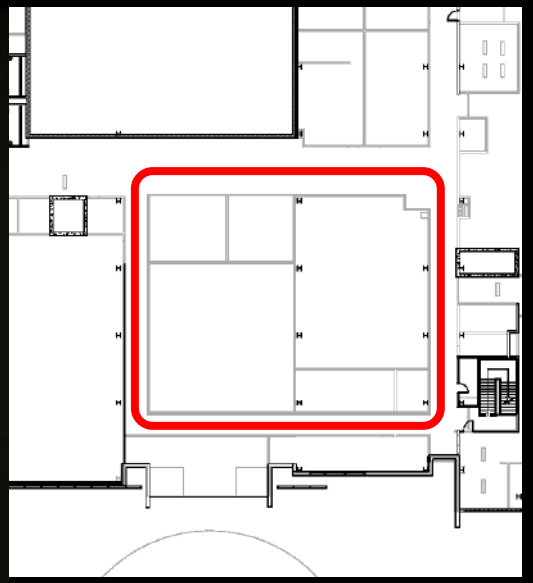
OpenSfM
+ Marker Tracks



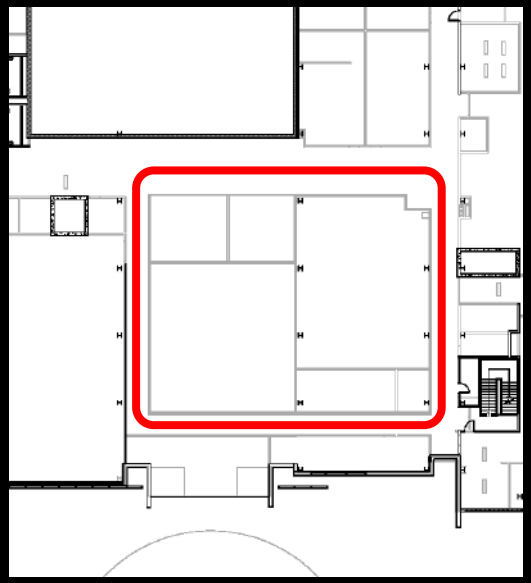
Marker Mapper
Pattern Recognition 2018

ECE Floor3 Loop

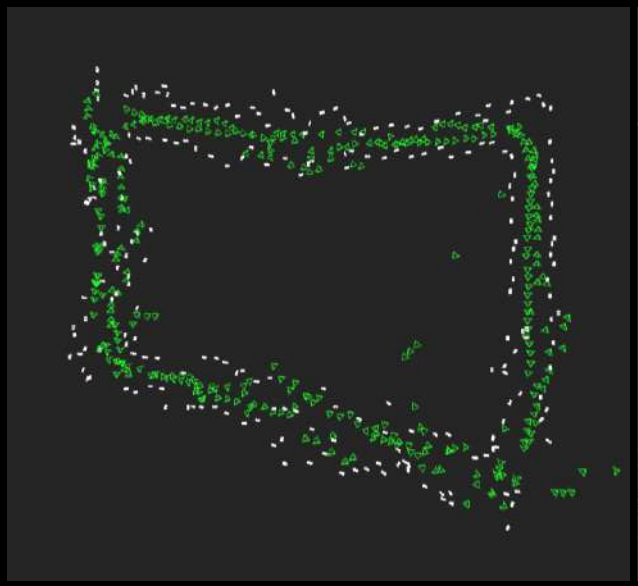




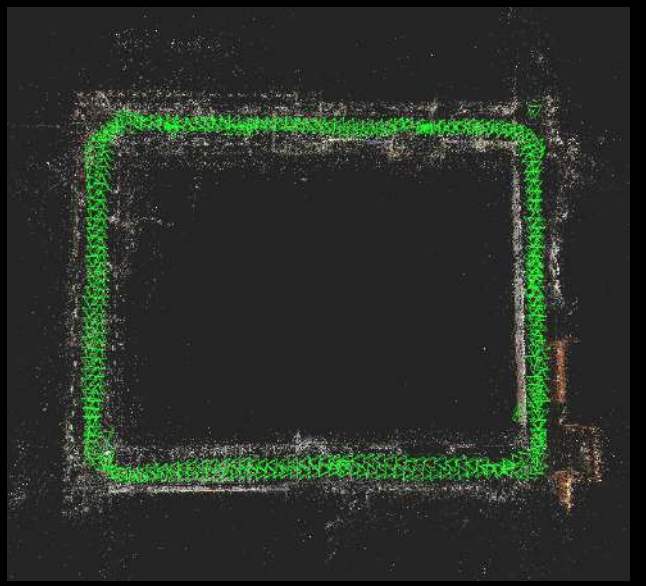
ECE Floor3 Loop

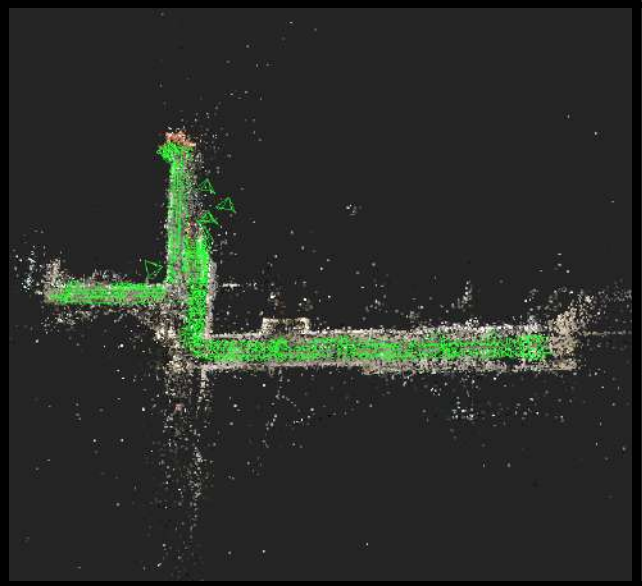


MarkerMapper

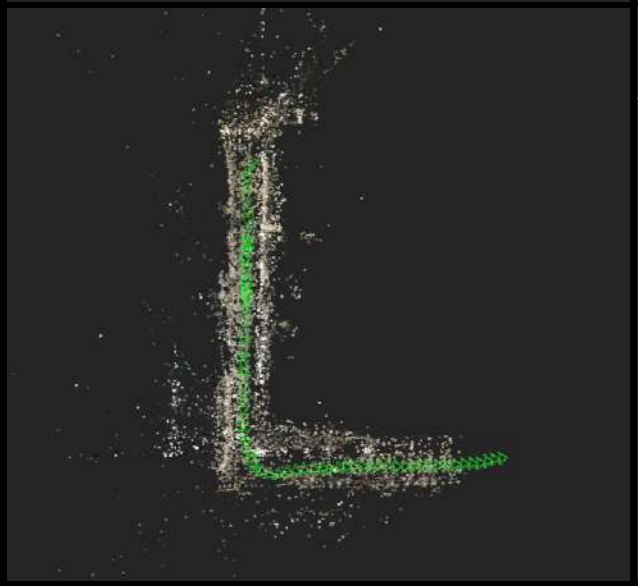


Our Method

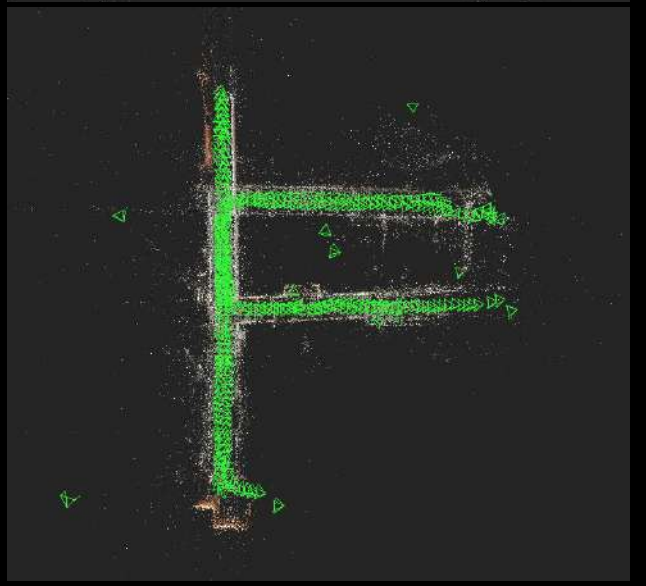




OpenSfM

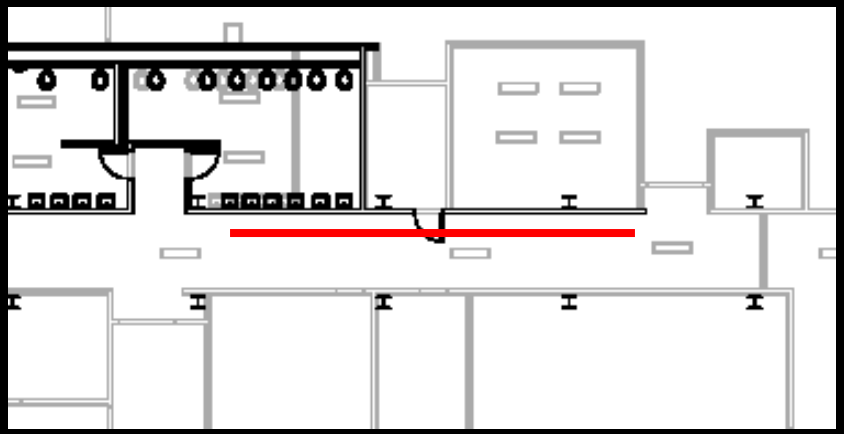


OpenSfM + Masking

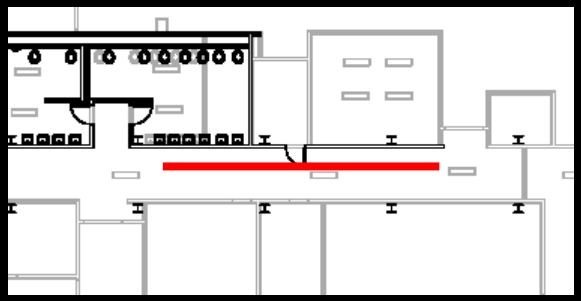


OpenSfM + Marker Tracks

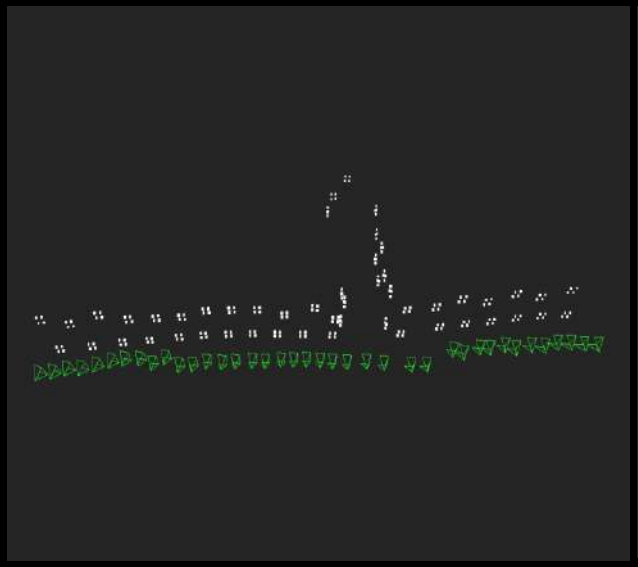
ECE Floor4 Wall



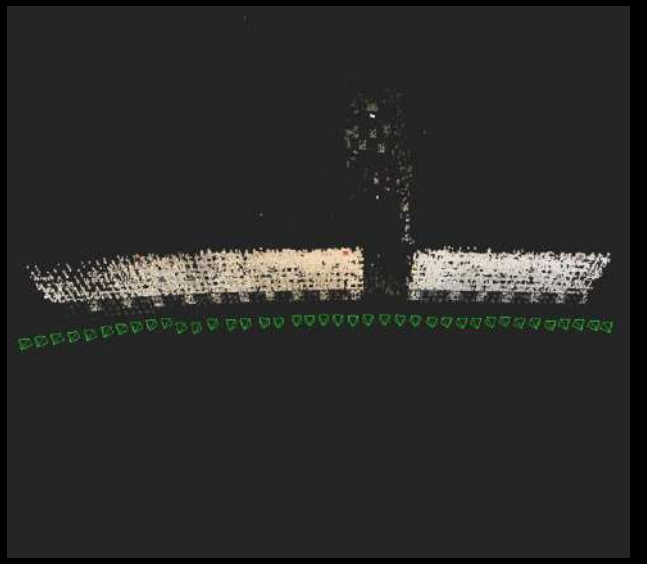
ECE Floor4 Wall

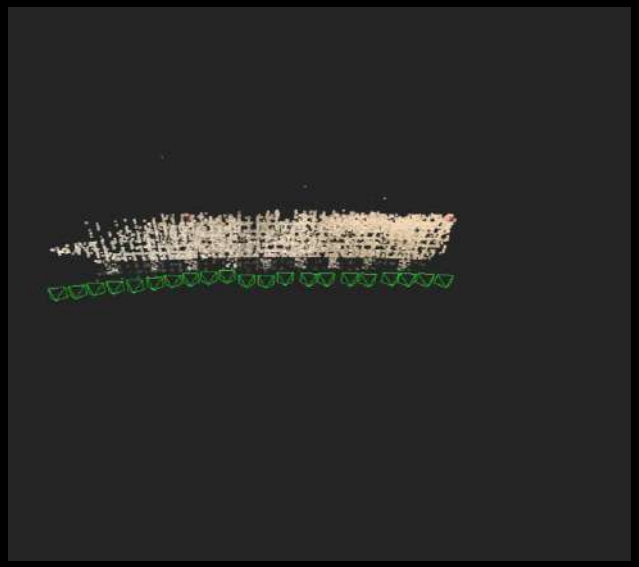


MarkerMapper

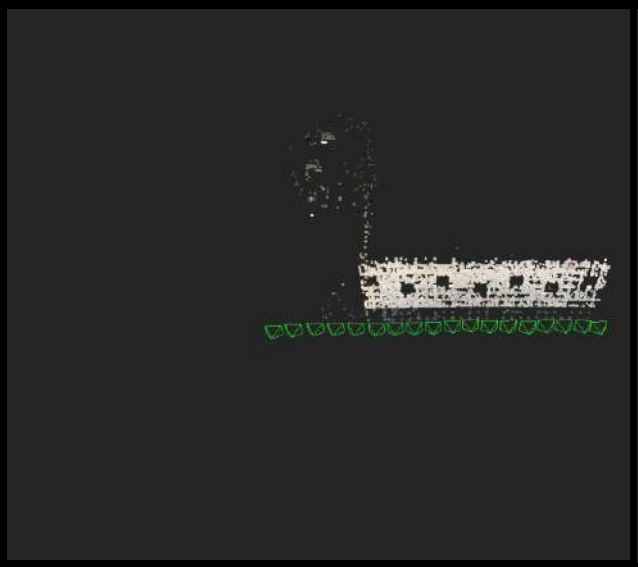


Our Method

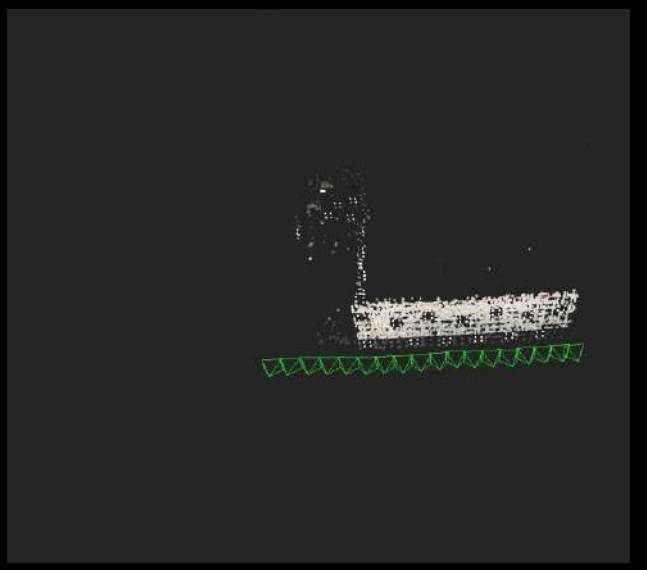




OpenSfM

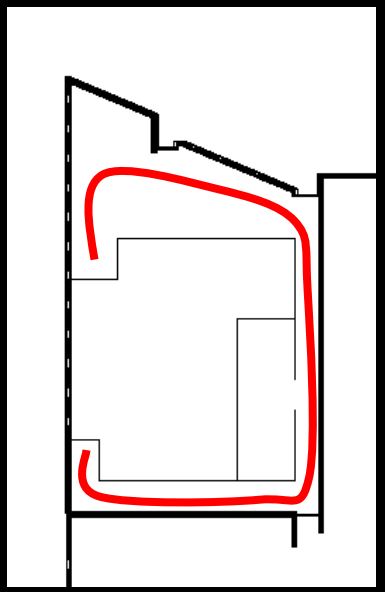


OpenSfM + Masking

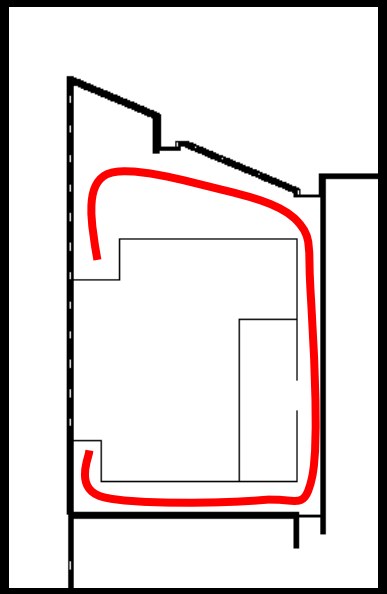


OpenSfM + Marker Tracks

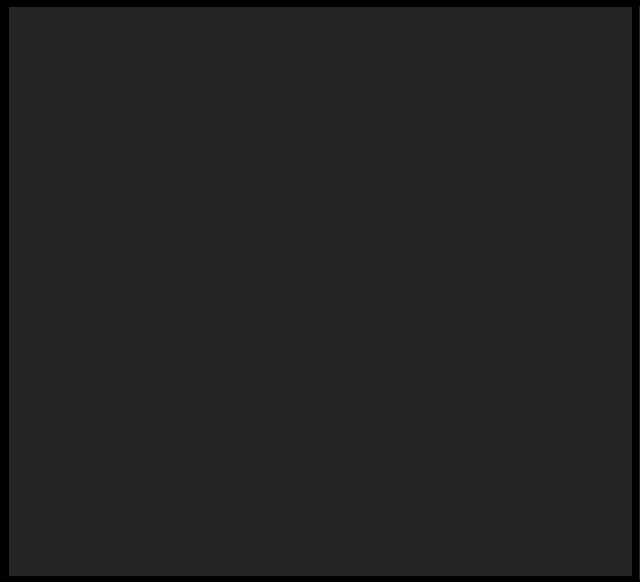
CEE Day CCW



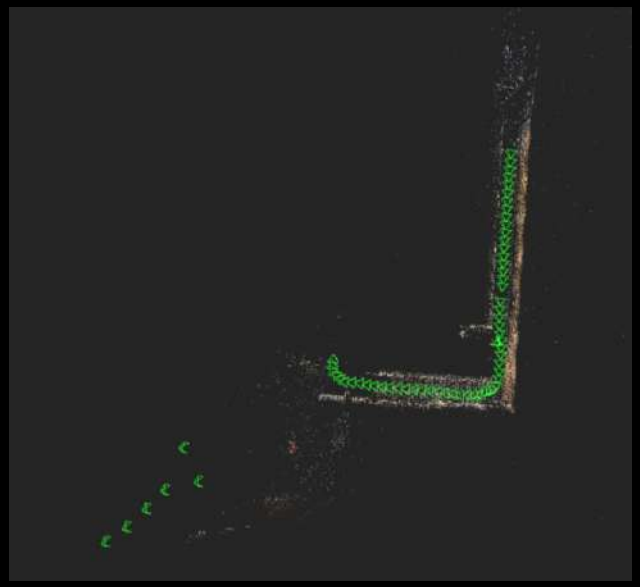
CEE Day CCW



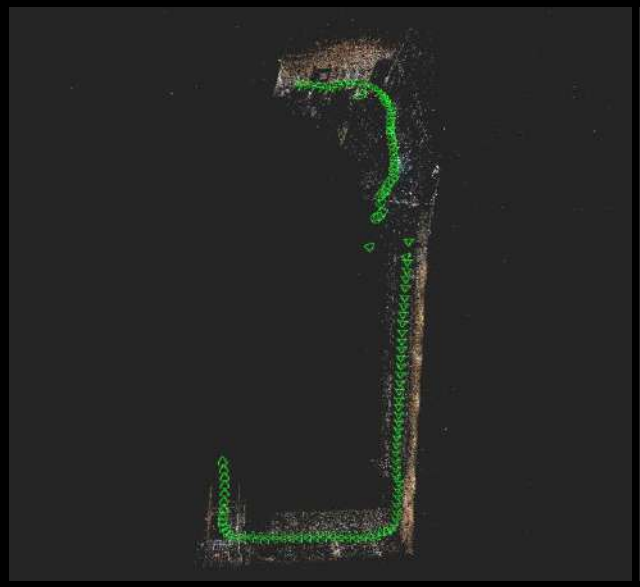
MarkerMapper



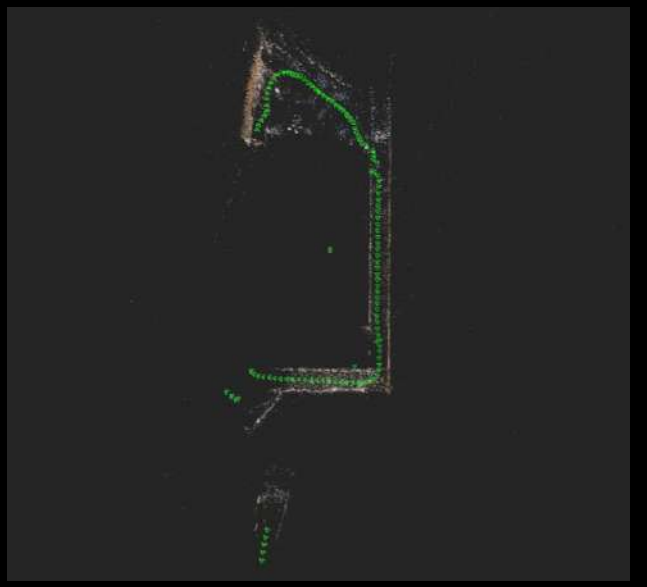
Our Method



OpenSfM

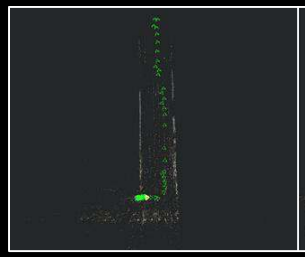
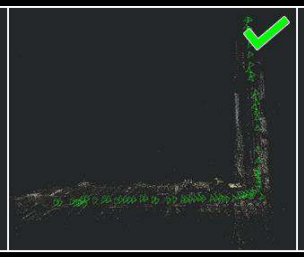
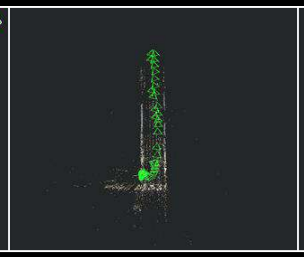
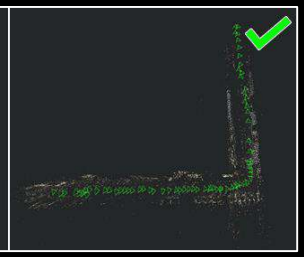
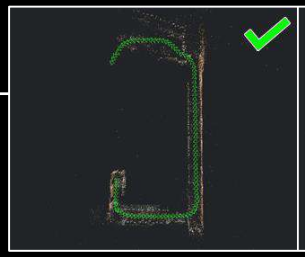
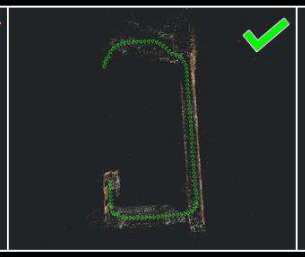
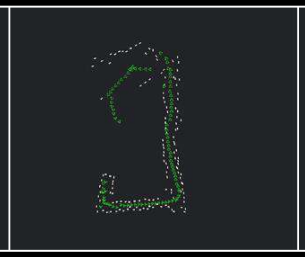
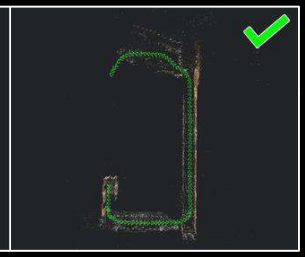


OpenSfM + Masking



OpenSfM + Marker Tracks

Results for all Datasets

	Images	Methods				
		OpenSfM	OpenSfM + Masking	OpenSfM + Marker Tracks	MarkerMapper	Our Method
ECE F2 Hall	74					
ECE F3 Loop CCW	192					
ECE F3 Loop CW	170					
ECE F3 Loop	362					
ECE F5 Hall	239					
ECE Stairs	89					
ECE F5 Stairs	328					
ECE F4 Wall	39					
CEE Day CW	63					
CEE Day CCW	120					
CEE Day	252					
CEE Night CW	96					
CEE Night CCW	79					
CEE Night	170					
MUF F2	896					
MUF F3	361					

Results for all Datasets

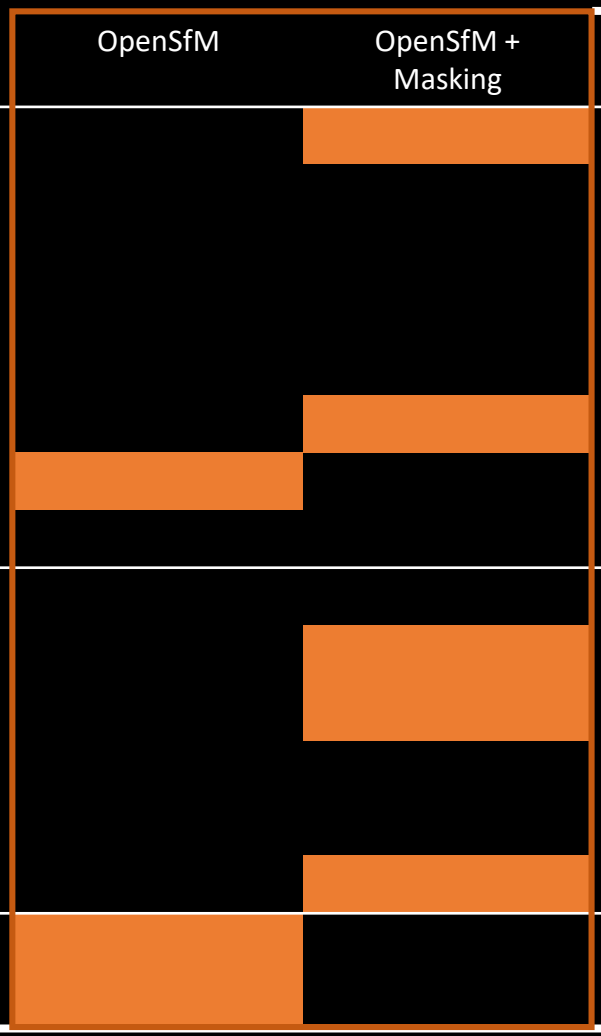
Our method performs as well or better than all other methods on all datasets

	Images	Methods				
		OpenSfM	OpenSfM + Masking	OpenSfM + Marker Tracks	MarkerMapper	Our Method
ECE F2 Hall	74					
ECE F3 Loop CCW	192					
ECE F3 Loop CW	170					
ECE F3 Loop	362					
ECE F5 Hall	239					
ECE Stairs	89					
ECE F5 Stairs	328					
ECE F4 Wall	39					
CEE Day CW	63					
CEE Day CCW	120					
CEE Day	252					
CEE Night CW	96					
CEE Night CCW	79					
CEE Night	170					
MUF F2	896					
MUF F3	361					
		3	4	2	4	16

Results for all Datasets

Masking markers is sometimes better than using markers as texture alone

	Images	Methods				
		OpenSfM	OpenSfM + Masking	OpenSfM + Marker Tracks	MarkerMapper	Our Method
ECE F2 Hall	74					
ECE F3 Loop CCW	192					
ECE F3 Loop CW	170					
ECE F3 Loop	362					
ECE F5 Hall	239					
ECE Stairs	89					
ECE F5 Stairs	328					
ECE F4 Wall	39					
CEE Day CW	63					
CEE Day CCW	120					
CEE Day	252					
CEE Night CW	96					
CEE Night CCW	79					
CEE Night	170					
MUF F2	896					
MUF F3	361					



Both Matching and Resectioning Matter

Both Matching and Resectioning improve results individually

	Mean % Images Registered
OpenSfM + Markers Masked	42.3 %
No Marker Informed Matching	49.8 %
No Marker Informed Resectioning	67.7 %
Full Method	98.4 %

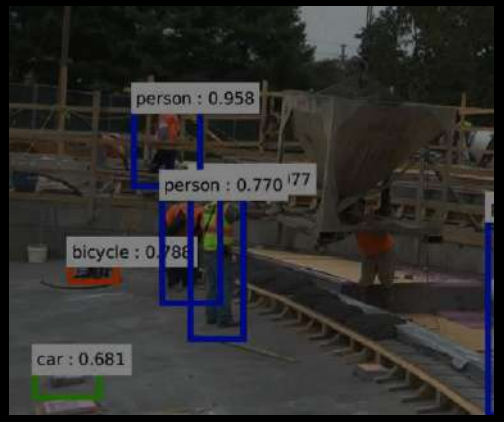
Best results when both are used together

Vision Based Robots Monitoring Built Environments

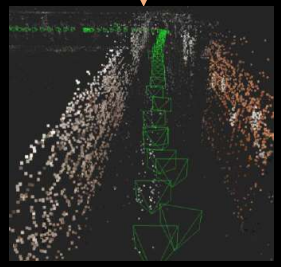
Data Capture

Mapping

Analysis



Structure from Motion



Simulating Features to
Predict Mapping Failure

FEATS: Synthetic Feature Tracks for Structure from Motion Evaluation

Joseph DeGol,
Jae Yong Lee,
Rajbir Kataria,
Daniel Yuan,
Timothy Bretl,
Derek Hoiem

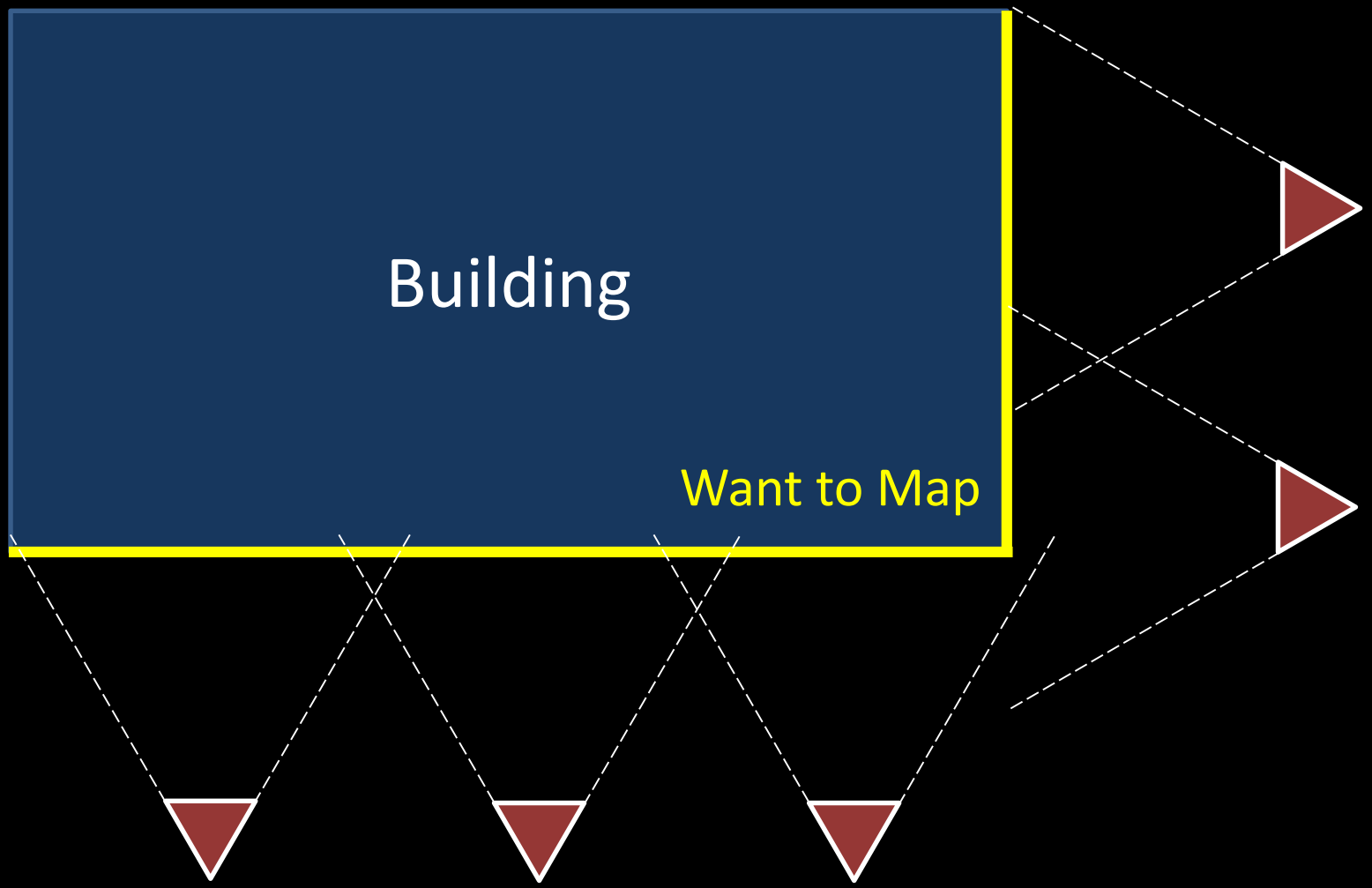
Submitted to ECCV 2018

Introduction

Feature Extraction And Tracking Simulator

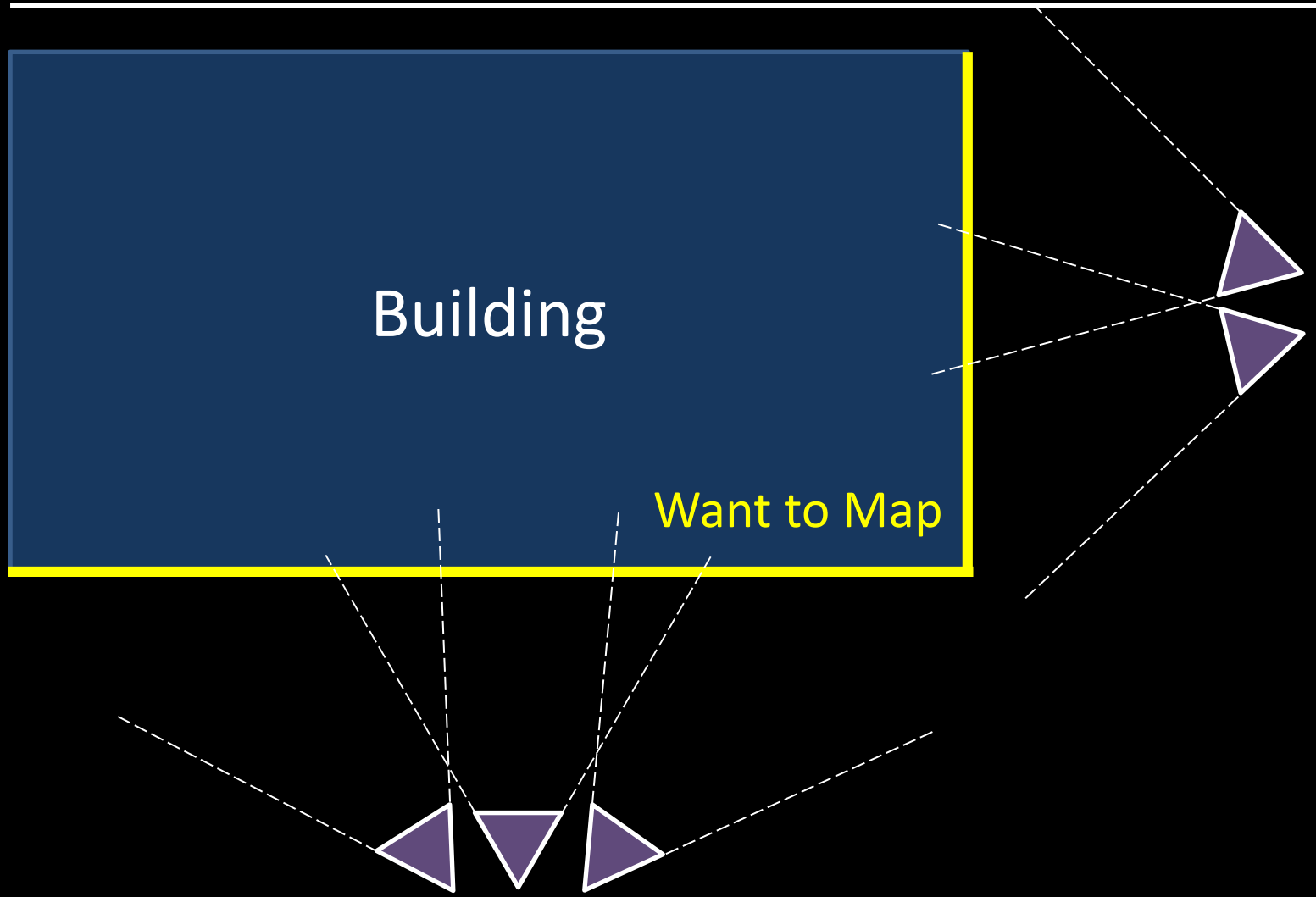
Image Collection Paths Can Lead to Failure

Image Collection Paths Can Lead to Failure



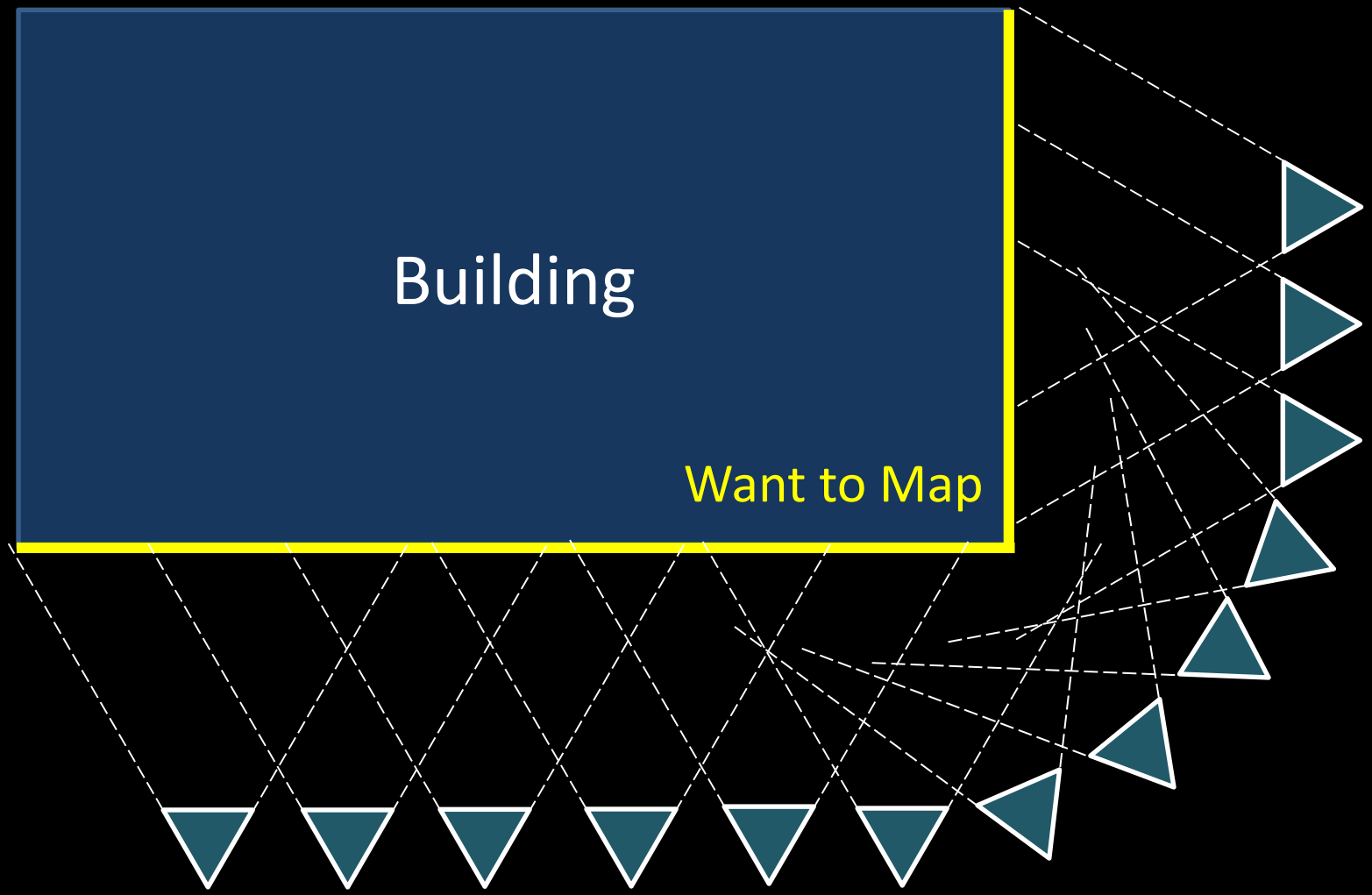
Not enough overlap between images

Image Collection Paths Can Lead to Failure



Not enough translation between images

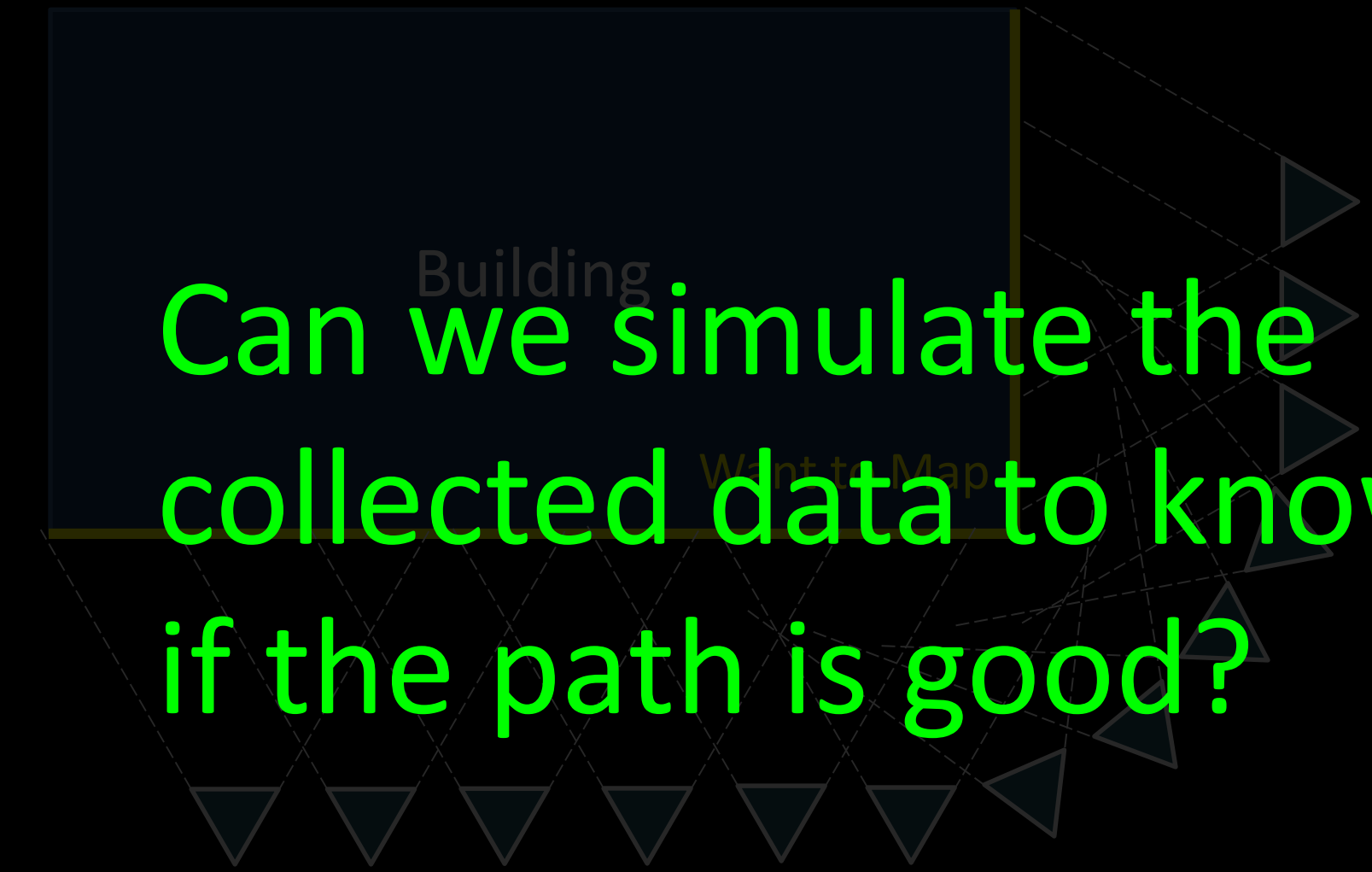
Image Collection Paths Can Lead to Failure



Intuition says this path is better

Do not know until after collection and processing

Image Collection Paths Can Lead to Failure



Can we simulate the collected data to know if the path is good?

Intuition says this path is better

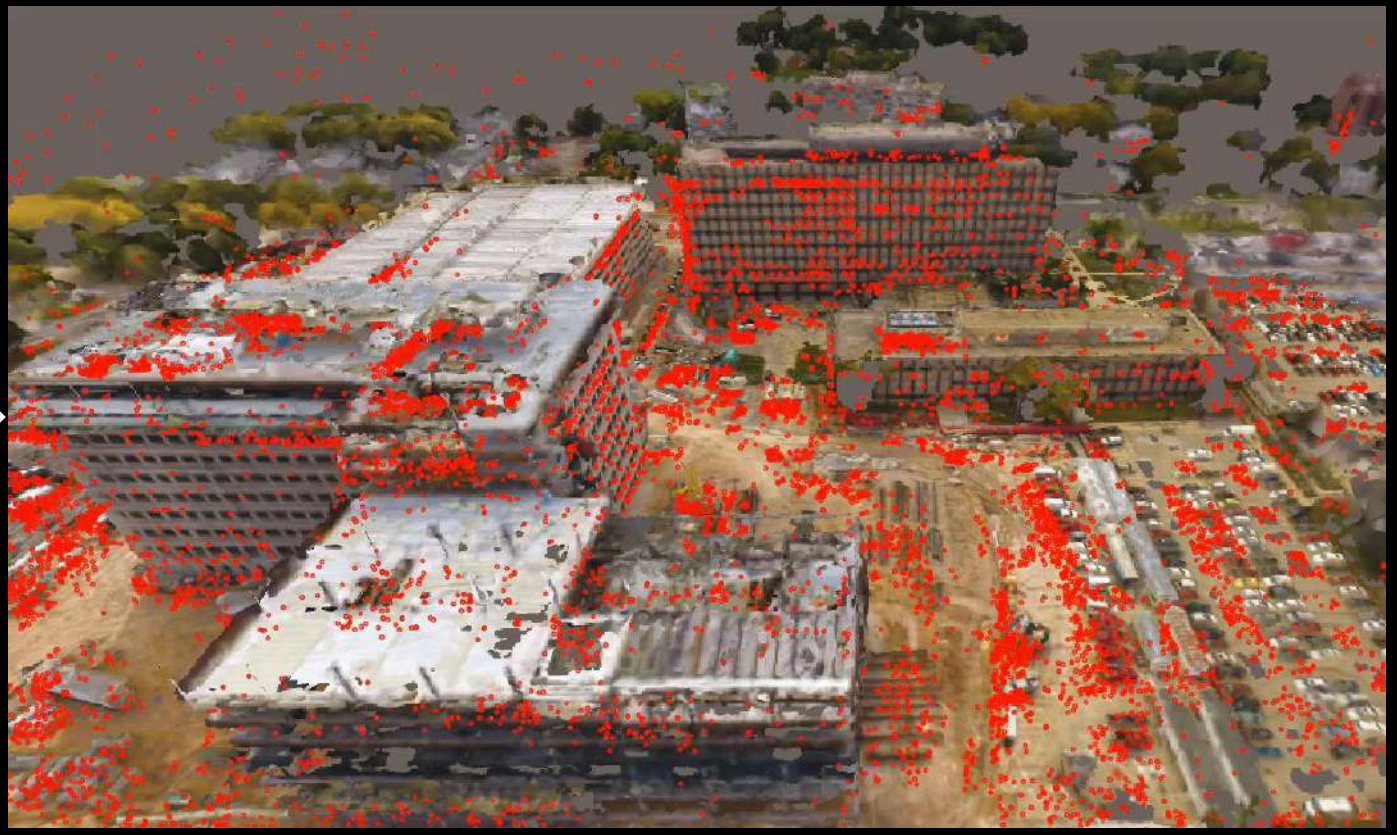
Do not know until after collection and processing

Simulating the Data Capture

Takes a user defined image path in a 3D map

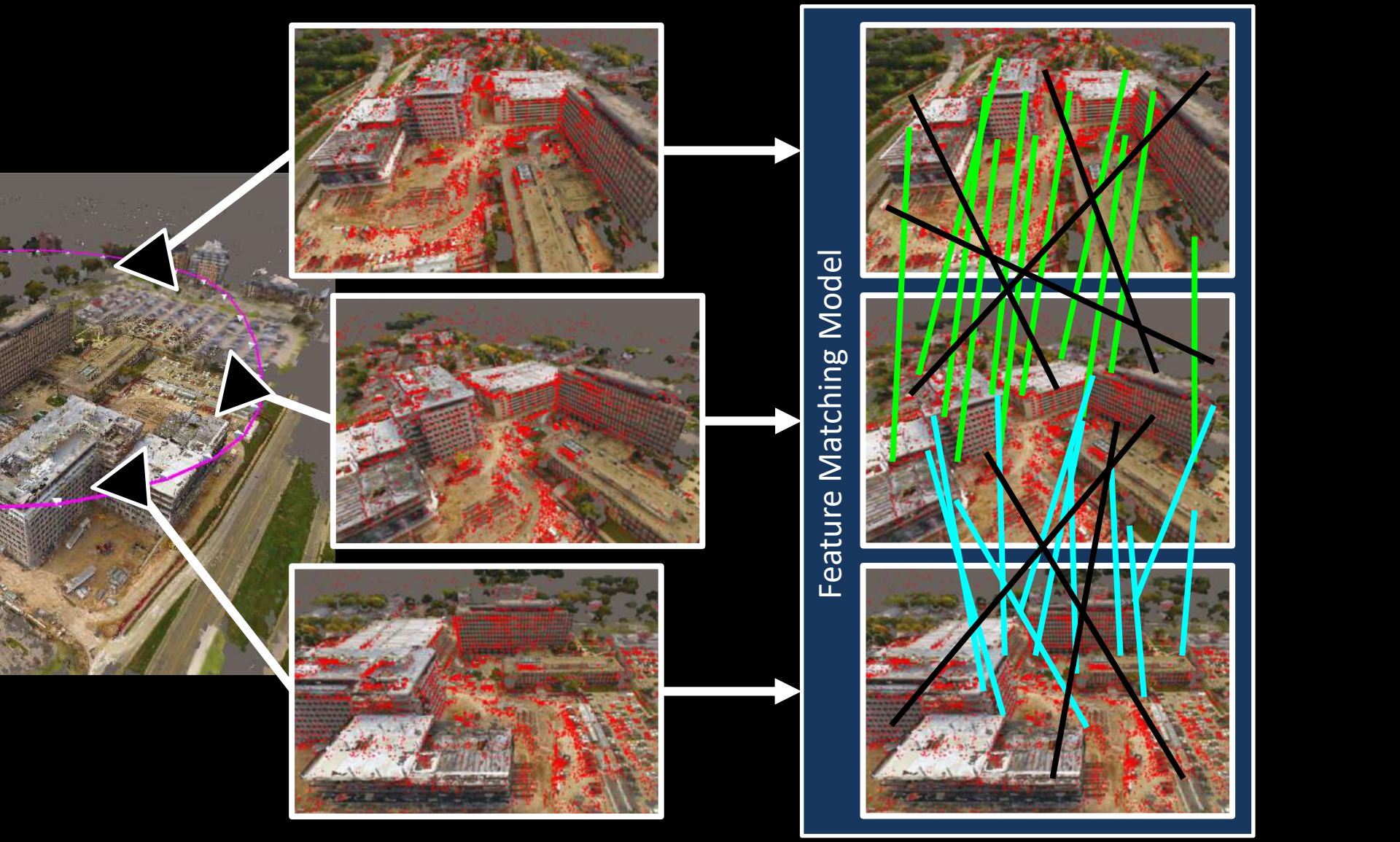
Simulating the Data Capture

Simulates Image Features for Images Along Path



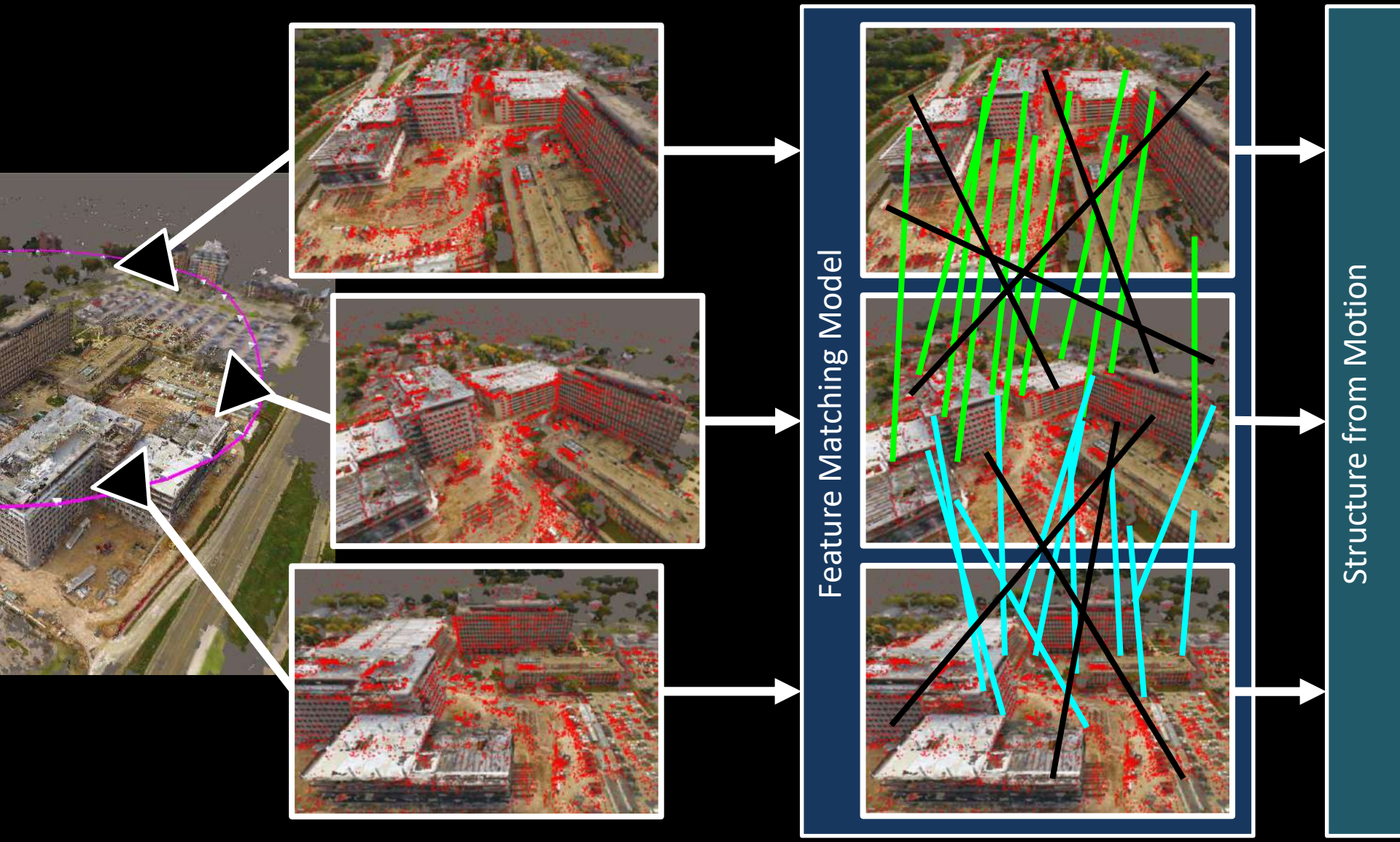
Simulating the Data Capture

Simulates Matching the Synthetic Features

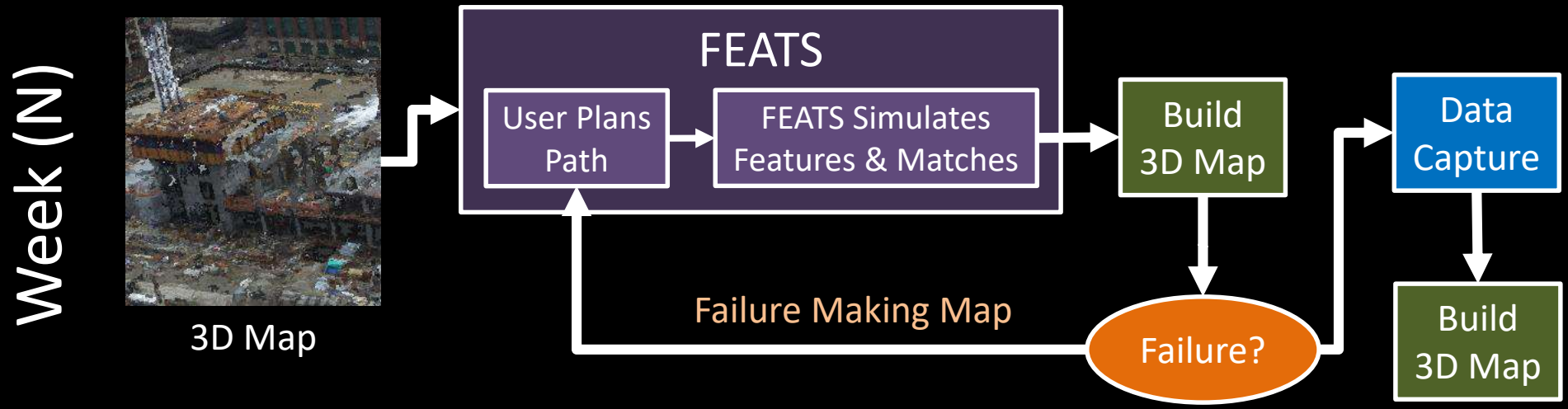


Simulating the Data Capture

Input Features and Matches (tracks) are ready to input to SfM



Example Workflow for FEATS



Example Workflow for FEATS

FEATS: Synthetic Feature Tracks for Structure from Motion Evaluation

Modeling Feature Noise

Modeling Feature Noise

For All Camera Pairs:

- For All 3D Points Seen by Both Cameras:

$$P_{Match} = P_{Scale}(S_\Delta) * P_{View}(V_\Delta) * P_{Roll}(R_\Delta)$$

  - If rand() < P_{Match} :
    - Add Noise for 2D Observations
    - Add Match for 3D Point
  - Add Bad Matches for Camera Pair

Modeling Feature Noise

For All Camera Pairs:

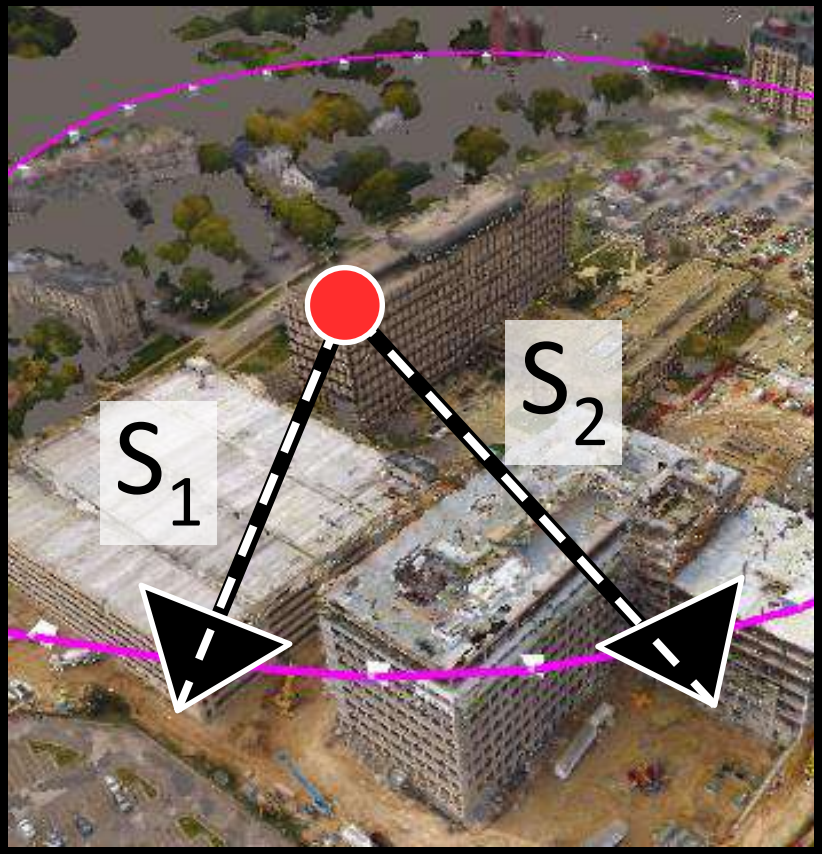
- For All 3D Points Seen by Both Cameras:

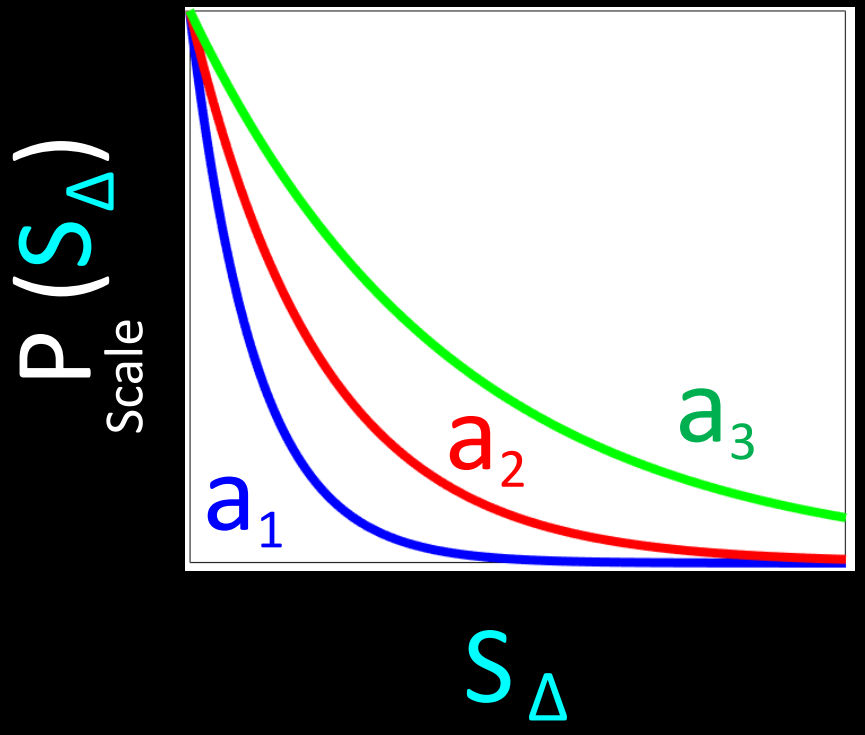
$$P_{Match} = P_{Scale}(S_{\Delta}) * P_{View}(V_{\Delta}) * P_{Roll}(R_{\Delta})$$

  - If rand() < P_{Match} :
    - Add Noise for 2D Observations
    - Add Match for 3D Point
- Add Bad Matches for Camera Pair

Differences in Scale Decrease Matching Probability

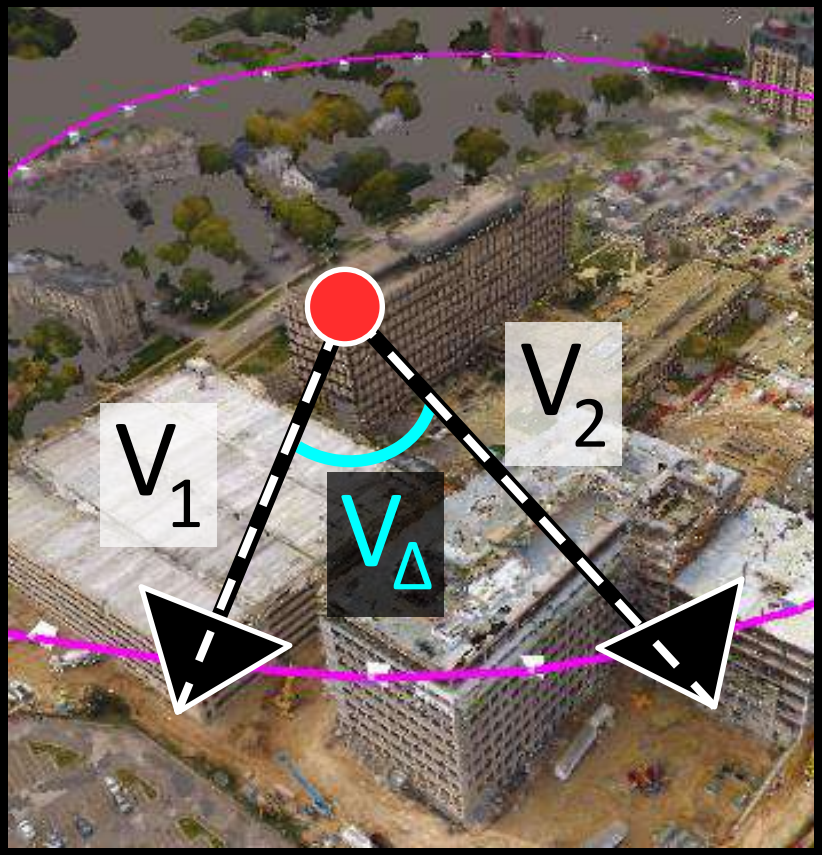
$$P_{Match} = P_{Scale}(S_\Delta) * P_{View}(V_\Delta) * P_{Roll}(R_\Delta)$$

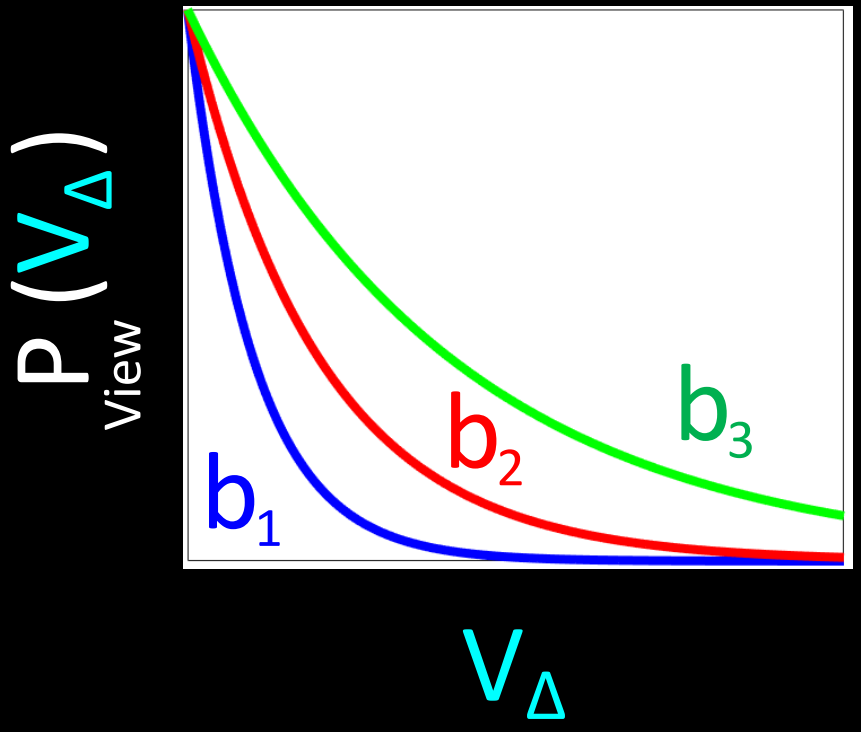




Differences in View Decrease Matching Probability

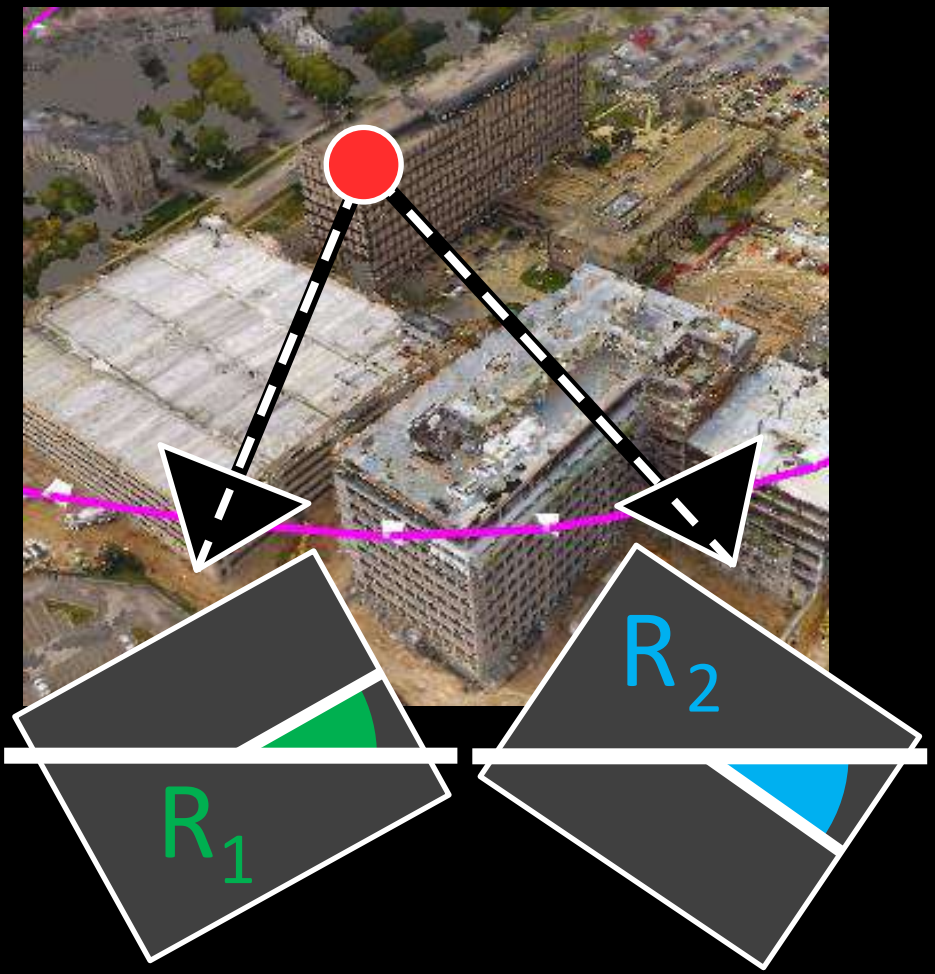
$$P_{Match} = P_{Scale}(S_\Delta) * P_{View}(V_\Delta) * P_{Roll}(R_\Delta)$$

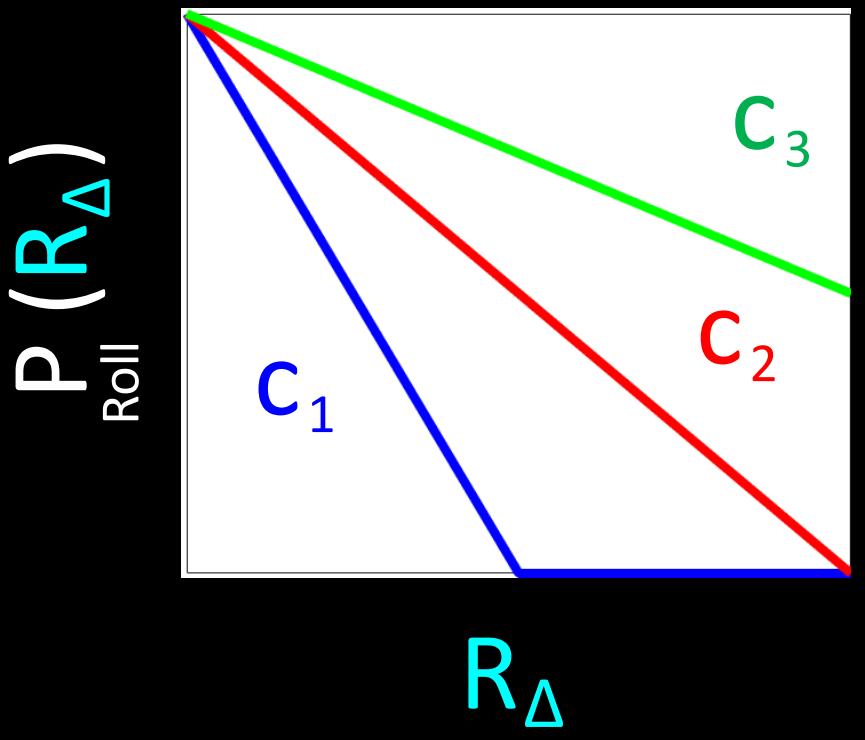




Differences in Roll Decrease Matching Probability

$$P_{Match} = P_{Scale}(S_\Delta) * P_{View}(V_\Delta) * P_{Roll}(R_\Delta)$$





Modeling Feature Noise

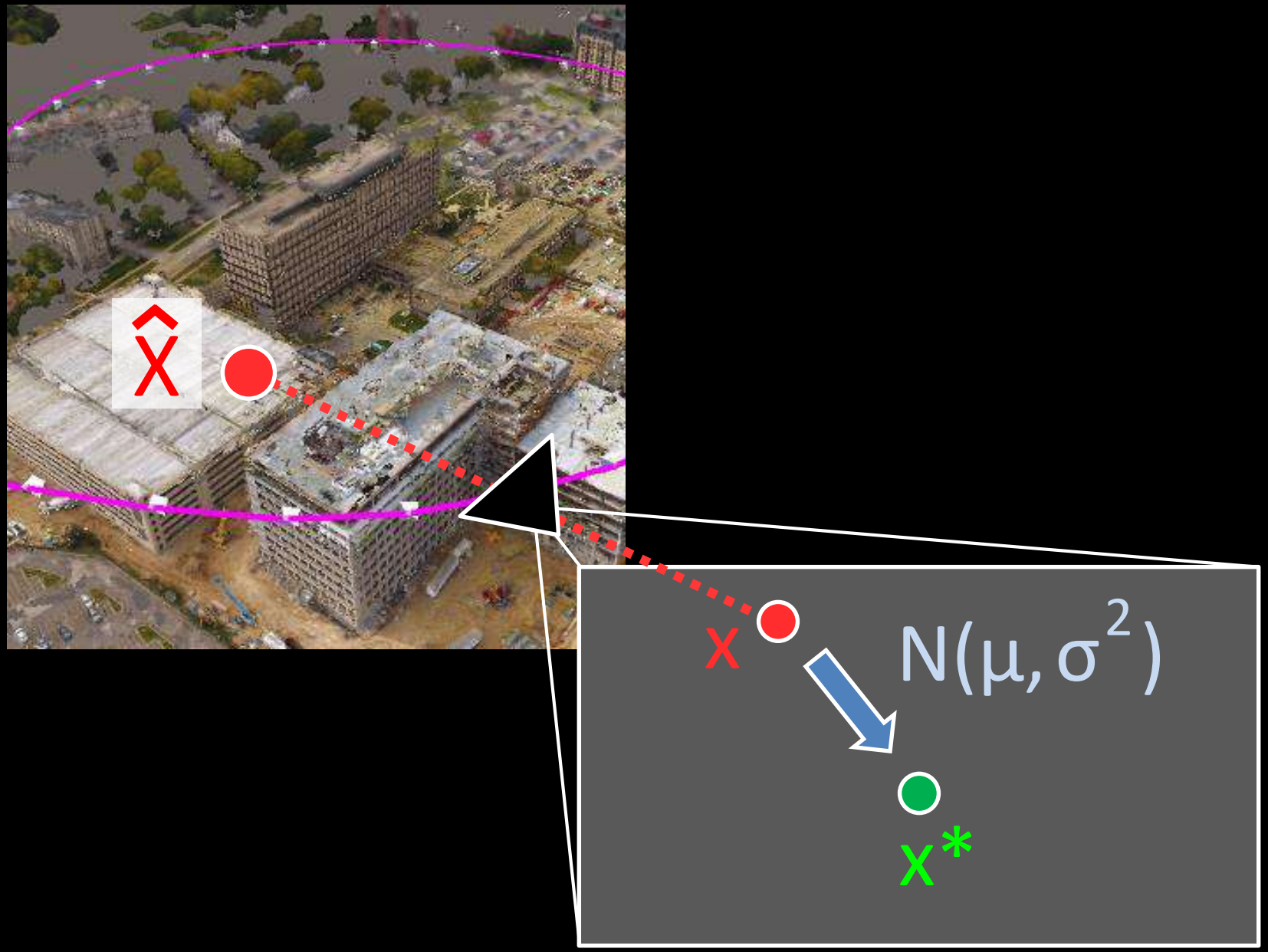
For All Camera Pairs:

- For All 3D Points Seen by Both Cameras:

$$P_{Match} = P_{Scale}(S_\Delta) * P_{View}(V_\Delta) * P_{Roll}(R_\Delta)$$

  - If rand() < P_{Match} :
    - Add Noise for 2D Observations
    - Add Match for 3D Point
- Add Bad Matches for Camera Pair

Add Noise for 2D Observations



Modeling Feature Noise

For All Camera Pairs:

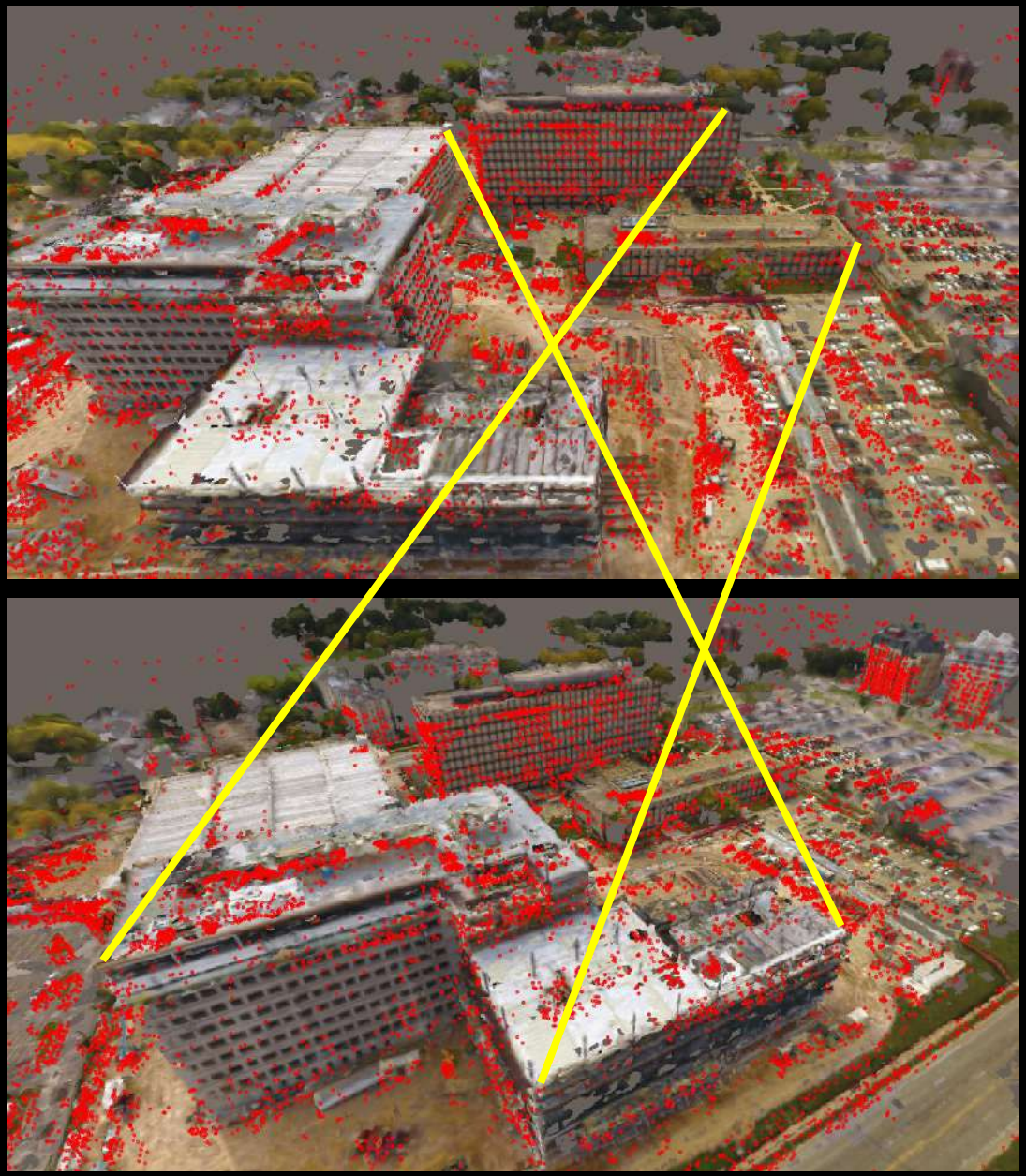
- For All 3D Points Seen by Both Cameras:

$$P_{Match} = P_{Scale}(S_\Delta) * P_{View}(V_\Delta) * P_{Roll}(R_\Delta)$$

  - If rand() < P_{Match} :
    - Add Noise for 2D Observations
    - Add Match for 3D Point
  - Add Bad Matches for Camera Pair

Feature Match Model: Bad Matches

Add bad matches

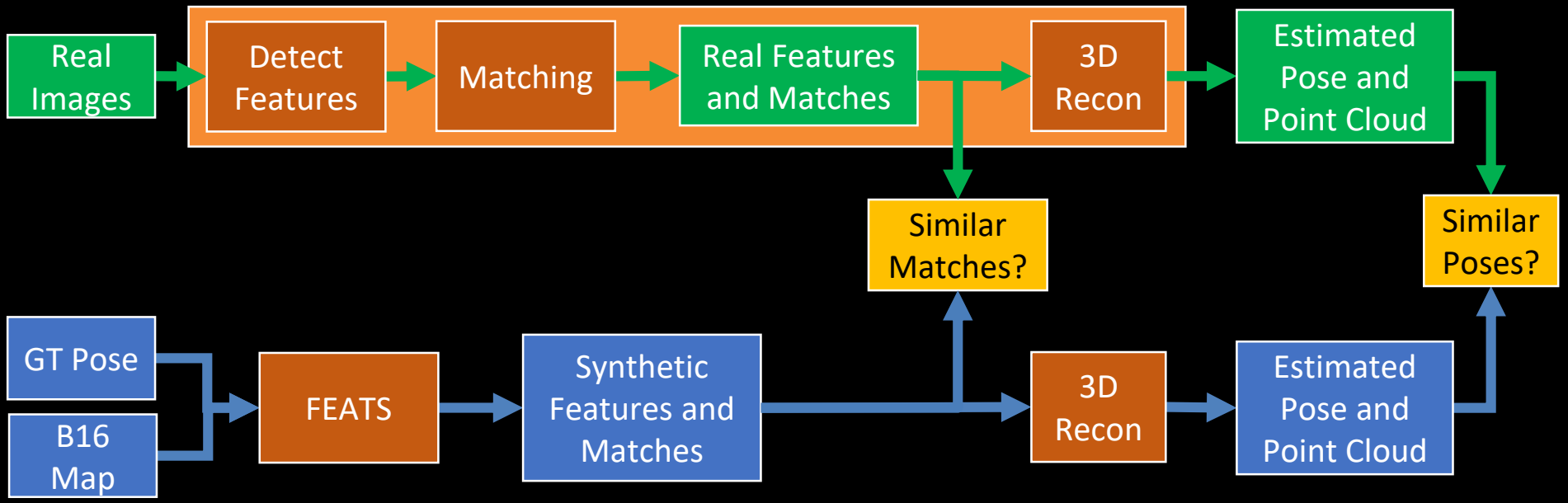


FEATS: Synthetic Feature Tracks for Structure from Motion Evaluation

Comparing to Real Data

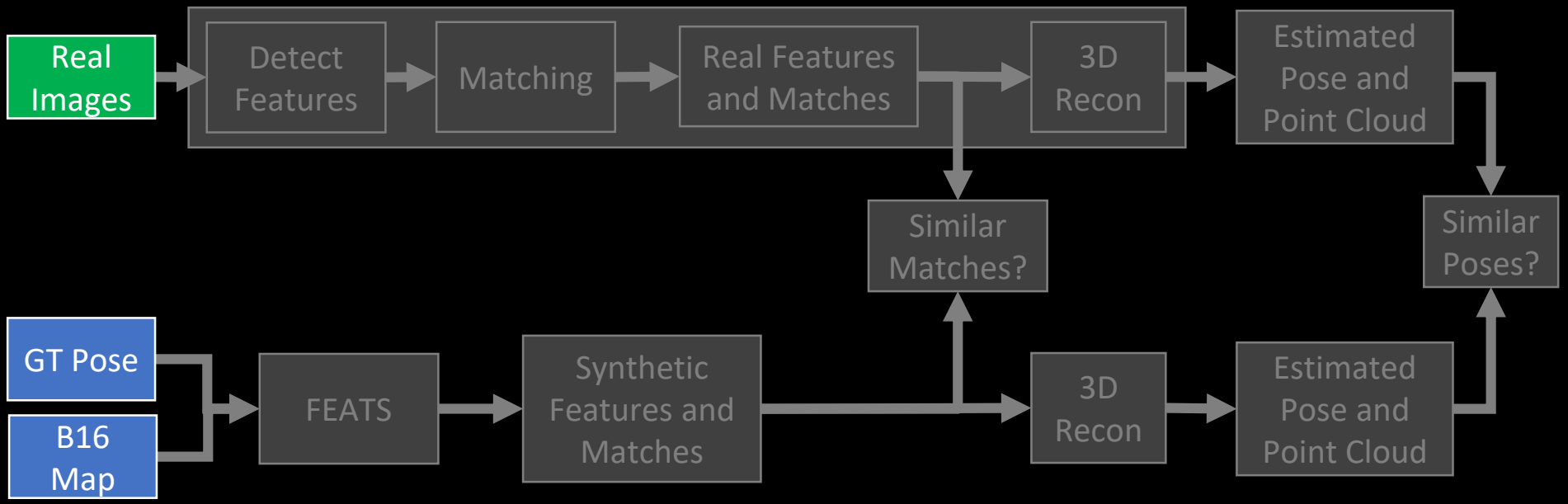
Validating the Simulator

Show that the simulator provides results representative of the real world.

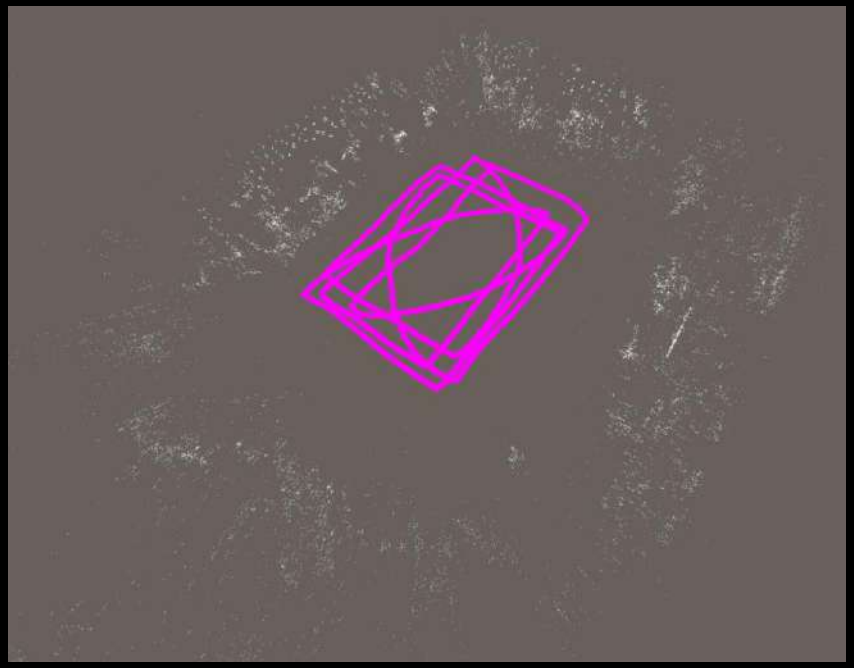


Validating the Simulator

Show that the simulator provides results representative of the real world.



Mapping B16



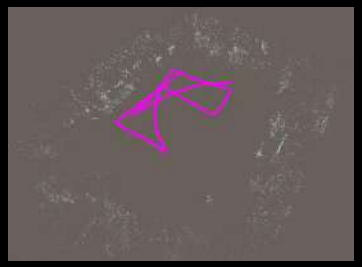
16 Validation Trajectories


Arc 1


Arc 2

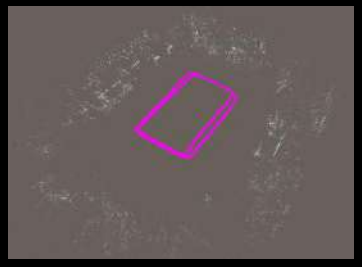

Arc 3


Egg


Long 1


Long 2


Long 3


Long 4

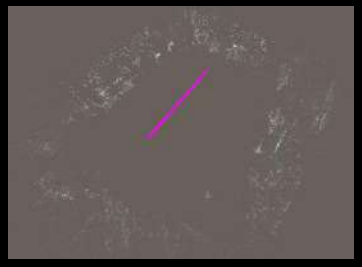

Long 5


Rotation Fast

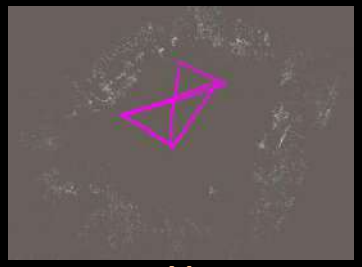

Rotation Slow


Snake 1


Snake 2


Straight 1

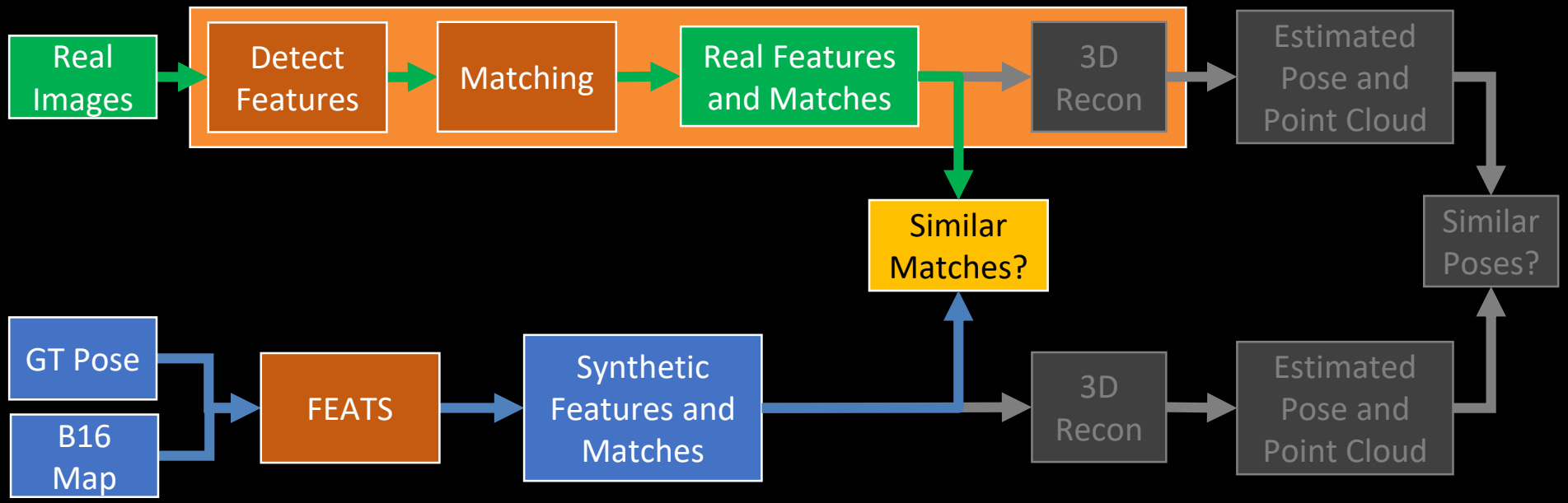

Straight 2

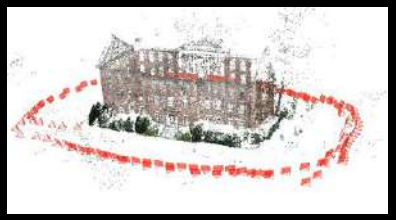

X

Images and Ground Truth Pose for each

Validating the Simulator

Show that the simulator provides results representative of the real world.





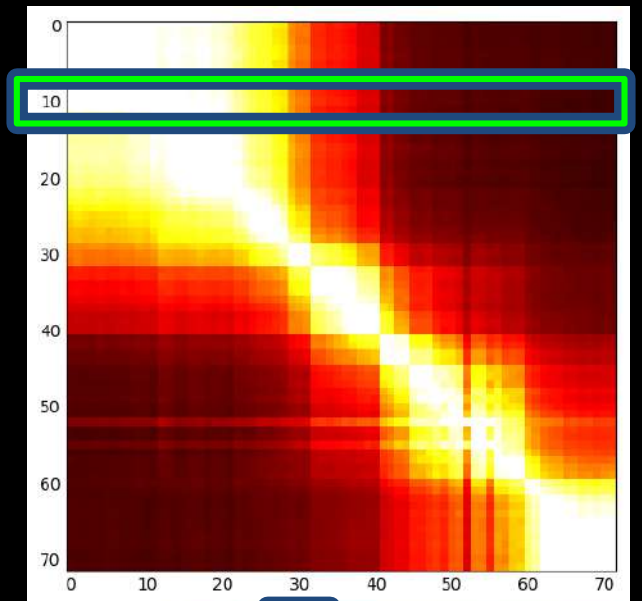
COLMAP
CVPR & ECCV 2016

OpenSfM
by Mappilary

VisualSfM
3DV 2013

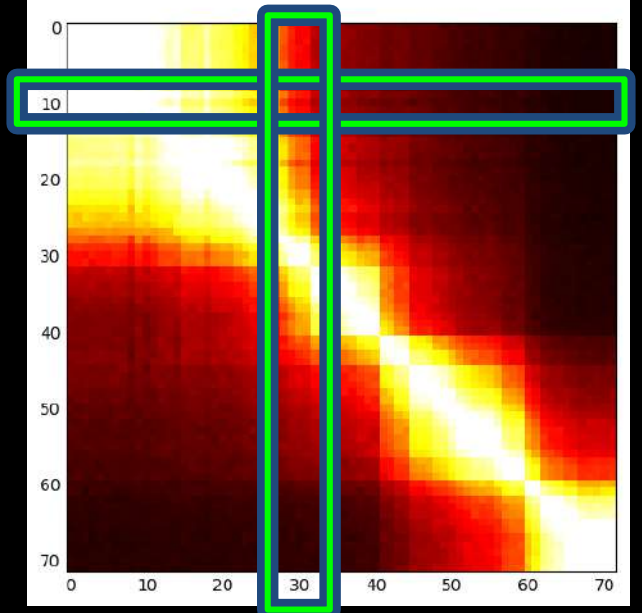
Verifying the Match Model

Real



Percent feature matches between image 10 and images 0 to 70

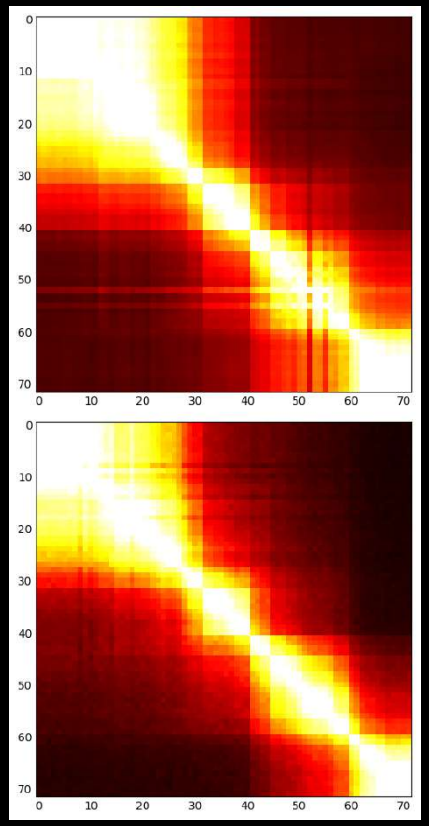
Synthetic



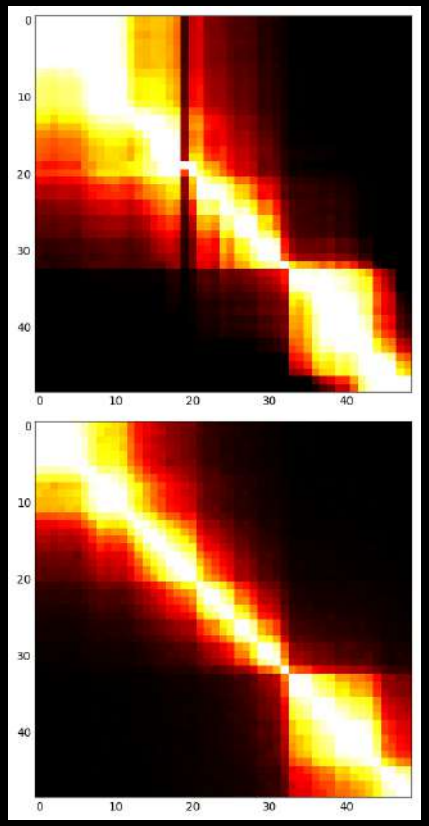
Percent feature matches between image 10 and image 30

Verifying the Match Model

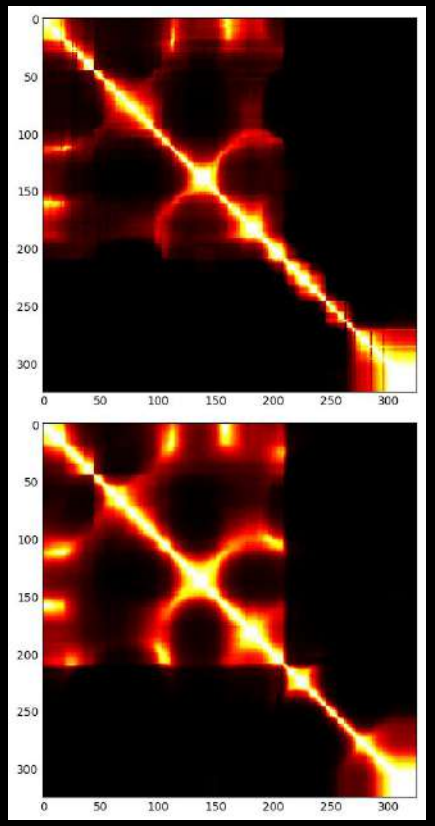
ALL correlations above +0.74



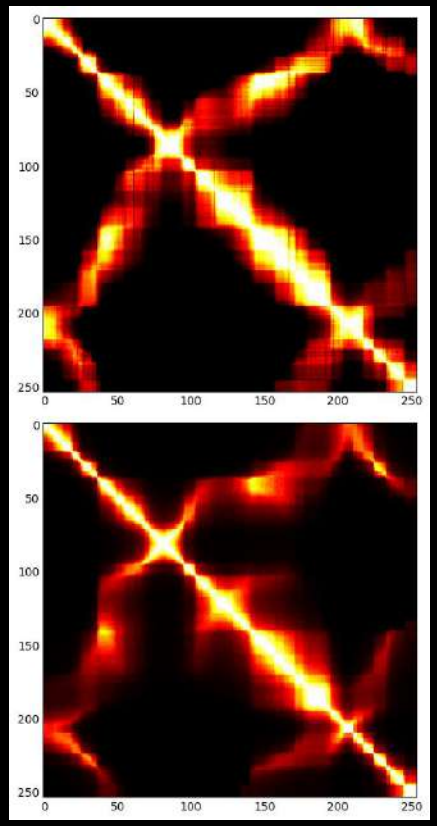
Straight 2 (OpenSfM)
0.98



Rot. Fast (COLMAP)
0.94



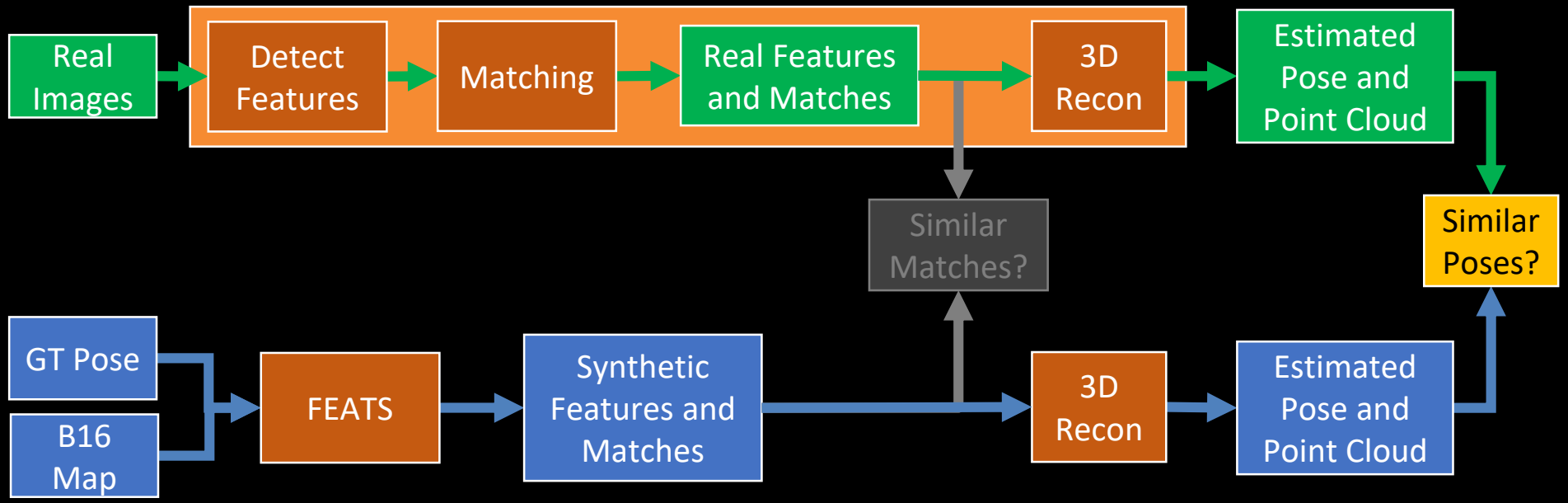
Long 3 (OpenSfM)
0.93

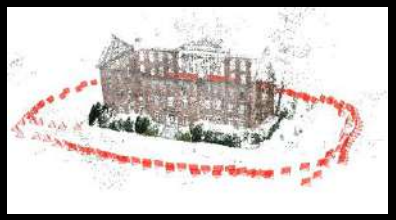


Long 5 (VisualSfM)
0.88

Validating the Simulator

Show that the simulator provides results representative of the real world.





COLMAP
CVPR & ECCV 2016

OpenSfM
by Mappilary

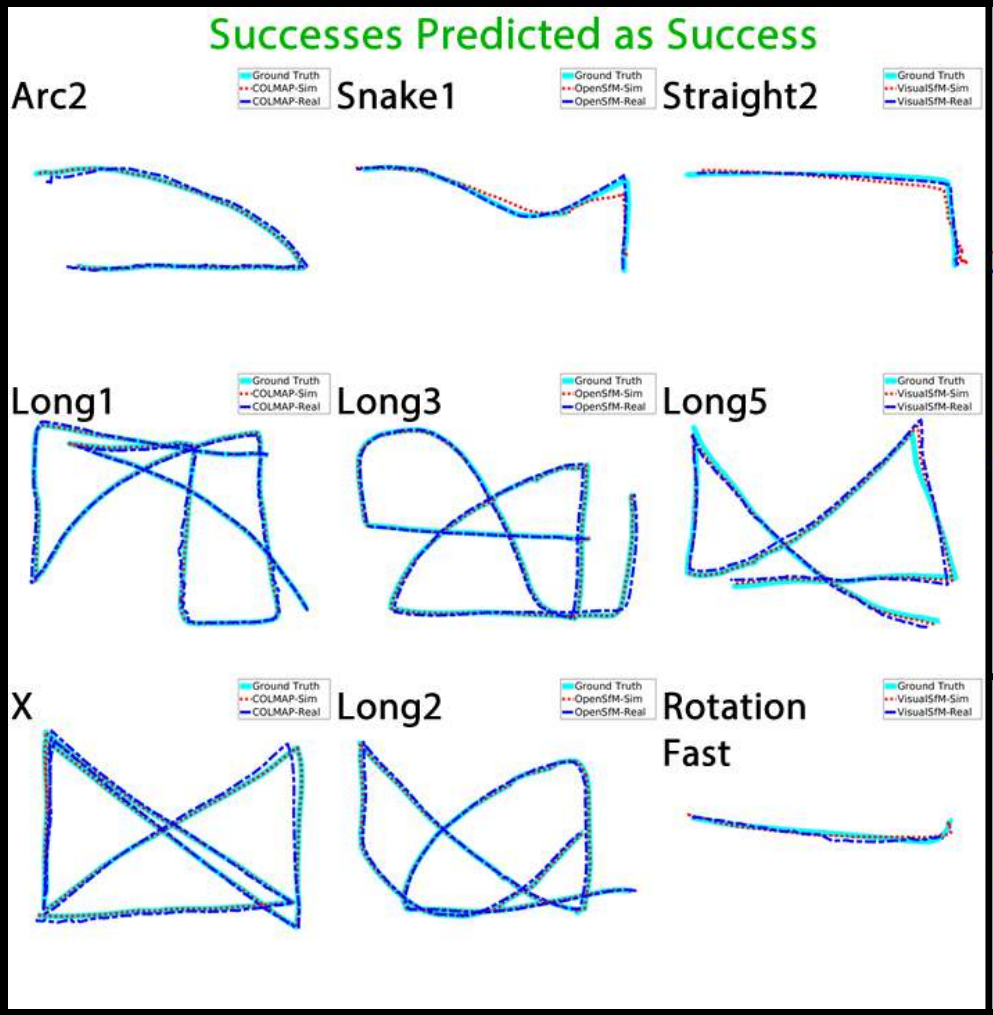
VisualSfM
3DV 2013

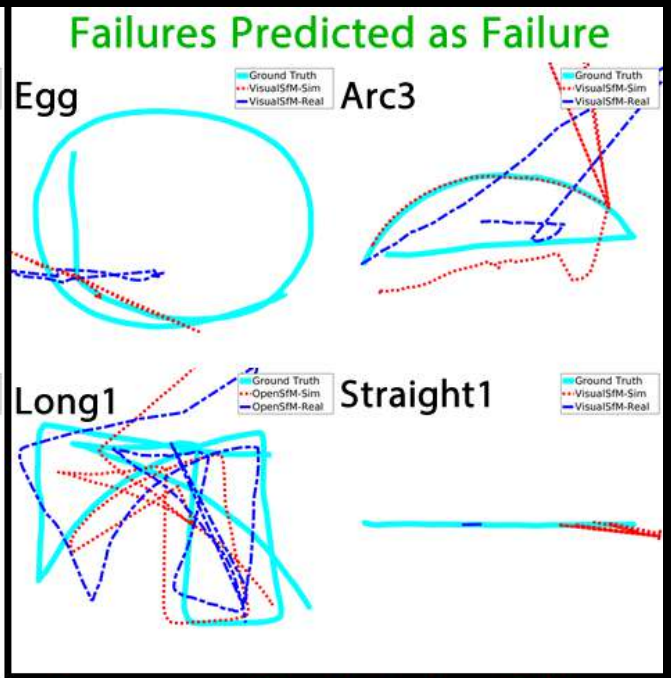
Verifying 48 Synthetic Reconstructions

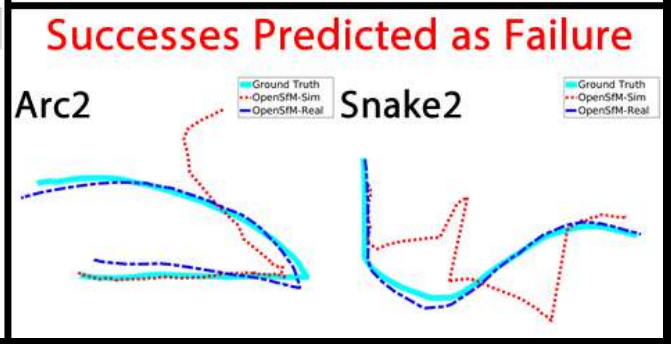
38 Successes Predicted as Success

8 Failures Predicted as Failure

2 Successes Predicted as Failure







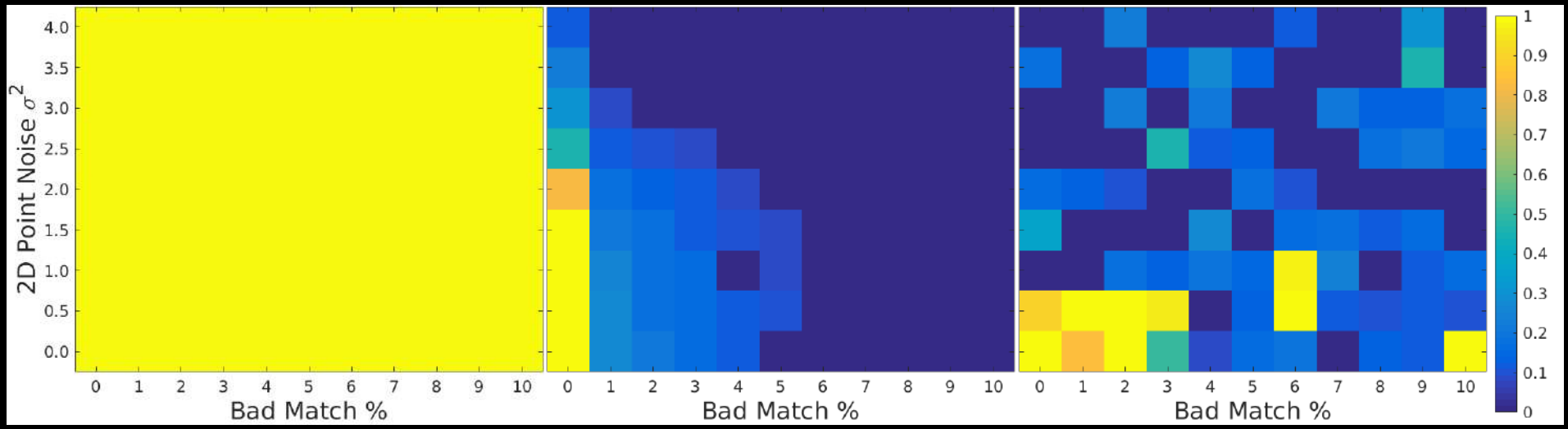
FEATS: Synthetic Feature Tracks for Structure from Motion Evaluation

New Evaluations

Varying Feature Noise and Bad Matches

FEATS provides control of noise parameters and hundreds of different trajectories can be generated quickly

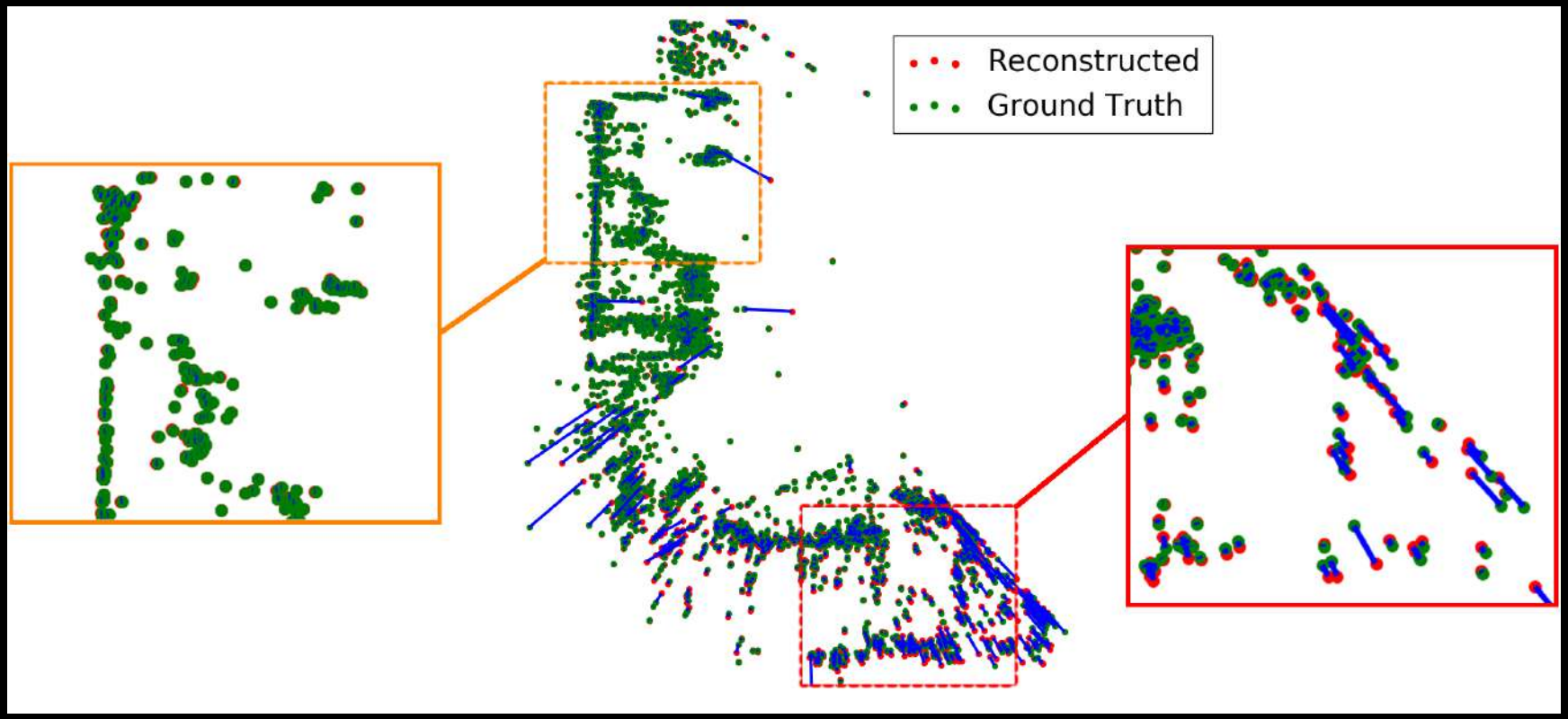
% Images Registered



COLMAP OpenSfM VisualSfM

3D Point Error

FEATS provides ground truth 3D location for each estimated 3D point

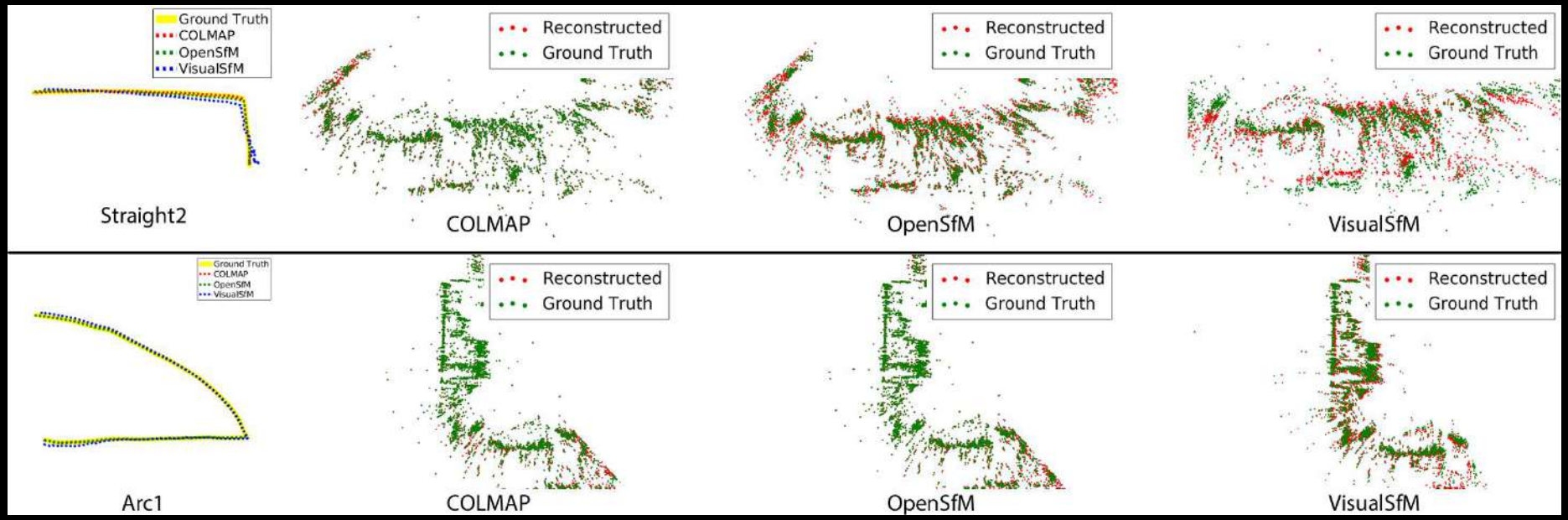


Traditional 3D geometry ground truth methods (Laser Scanners) do not

3D Point Error

Similar trajectory errors

Different geometry errors



	COLMAP	OpenSfM	VisualSfM
Arc 1	21.5 mm	26.0 mm	84.7 mm
Straight 2	27.2 mm	118.1 mm	246.8 mm

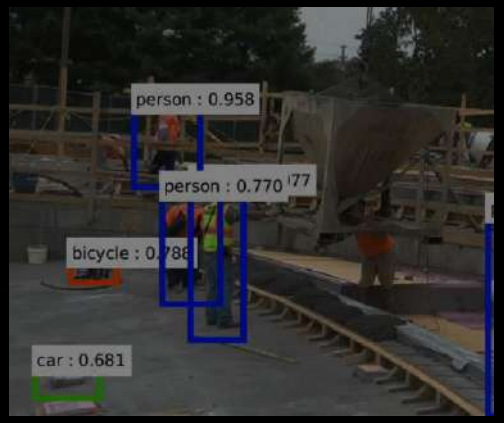
Metrics to evaluate 3D point error are important

Vision Based Robots Monitoring Built Environments

Data Capture

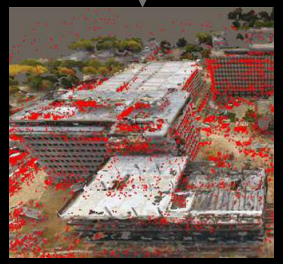
Mapping

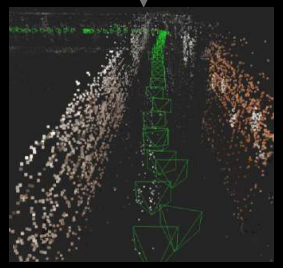
Analysis



SLAM

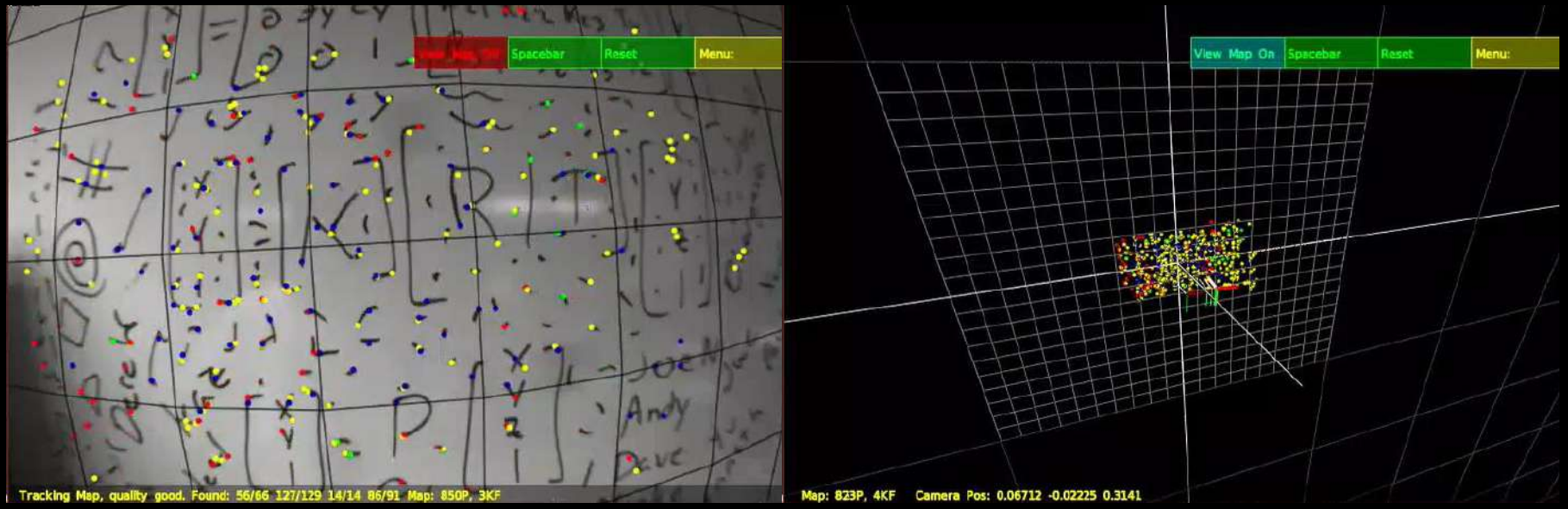
Structure from Motion





Simultaneous Localization And Mapping

- SLAM also does 3D Reconstruction
- SLAM runs in real time on video
- SfM runs offline on unordered images



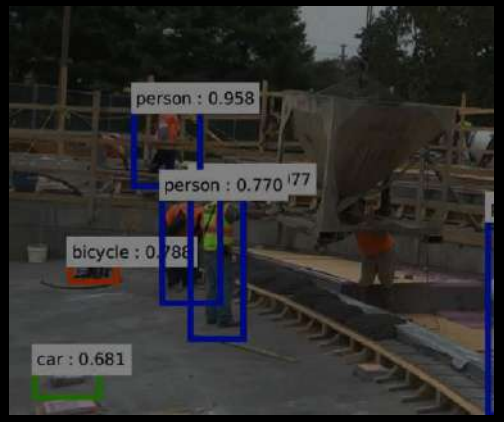
SLAM Fails When Few Features Are Trackable

Vision Based Robots Monitoring Built Environments

Data Capture

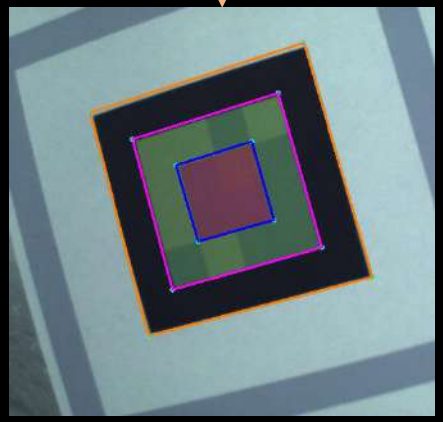
Mapping

Analysis



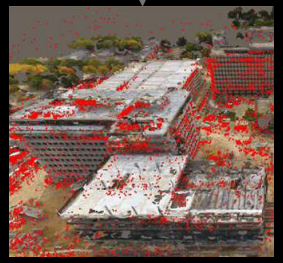
SLAM

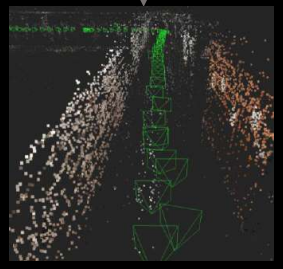
Overcoming Failures



A Colored Marker and Fast Detection Algorithm

Structure from Motion





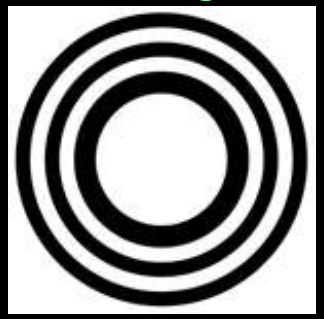
ChromaTag: A Colored Fiducial Marker and Fast Detection Algorithm

Joseph DeGol,
Timothy Bretl,
Derek Hoiem

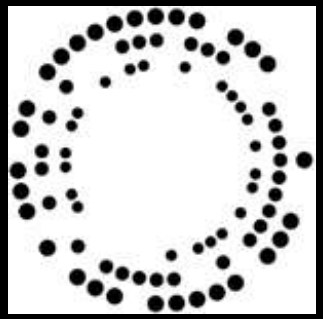
ICCV 2017

ChromaTag: A Marker for SLAM

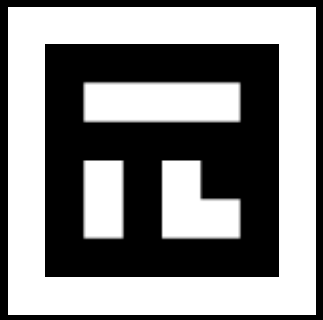
CCTag



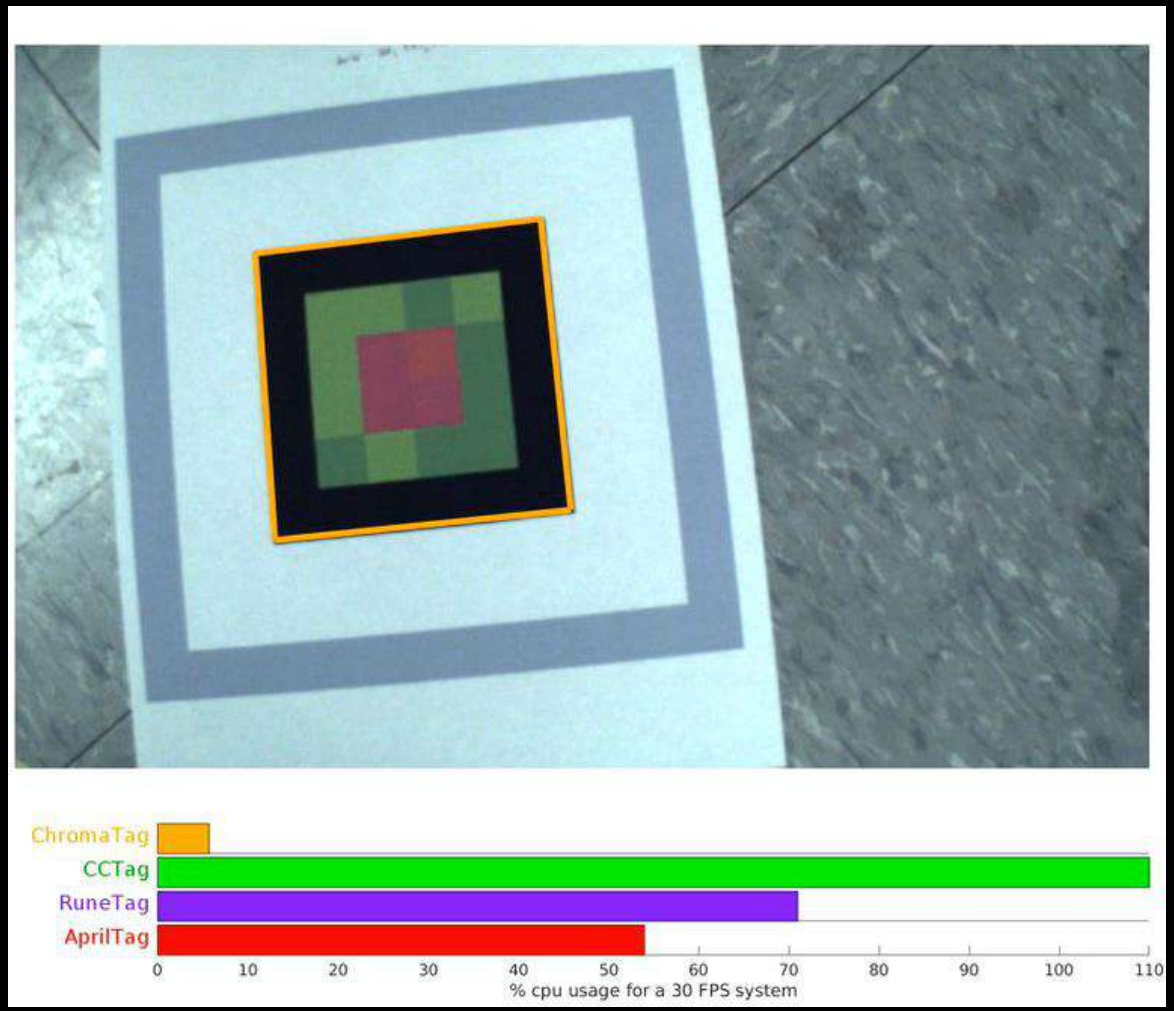
RuneTag



AprilTag



Other markers are too slow for SLAM



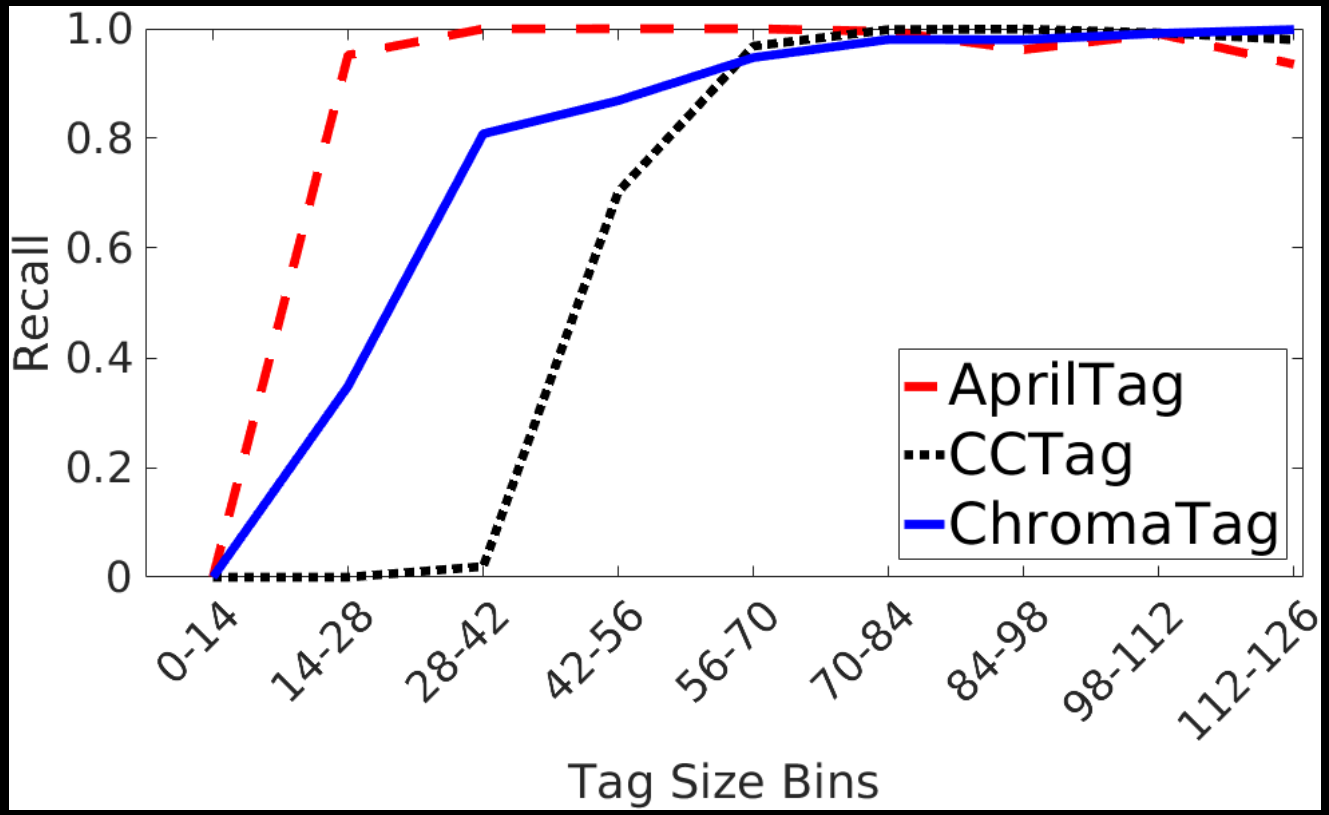
Average Frames Per Second

ChromaTag is significantly faster than AprilTag, CCTag, and RuneTag for both >0 and 0 detections.

	Average Frames Per Second		
	Total	> 0 Detections	0 Detections
ChromaTag	926	709	2616
AprilTag	56	56	49
CCTag	10	7	19
RuneTag	42	2	71

Recall vs. Tag Size and Viewing Angle

Recall > 80% after 30*30 pixel tag size



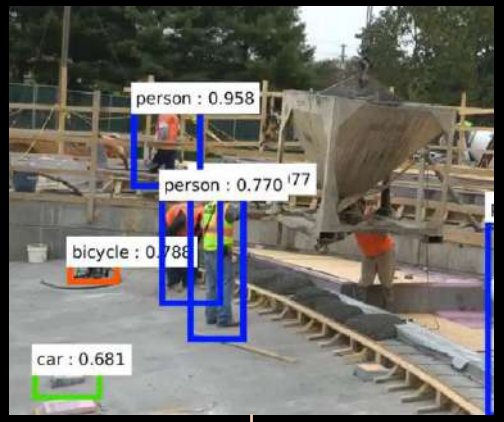
Precision is ~96%

Vision Based Robots Monitoring Built Environments

Data Capture

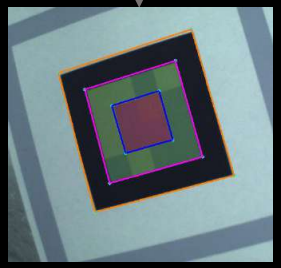
Mapping

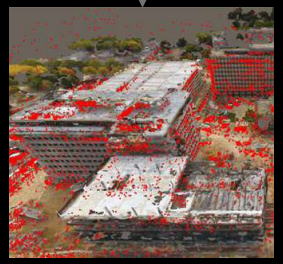
Analysis

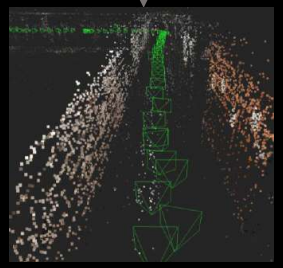


SLAM

Structure from Motion







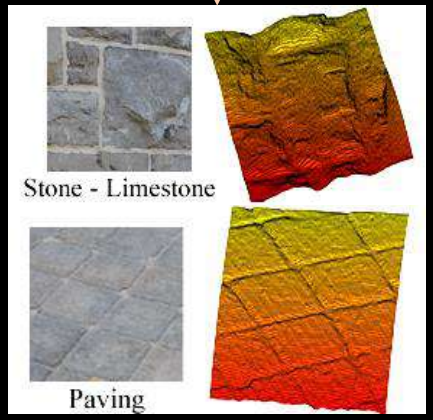


Image and Geometry for Material Recognition

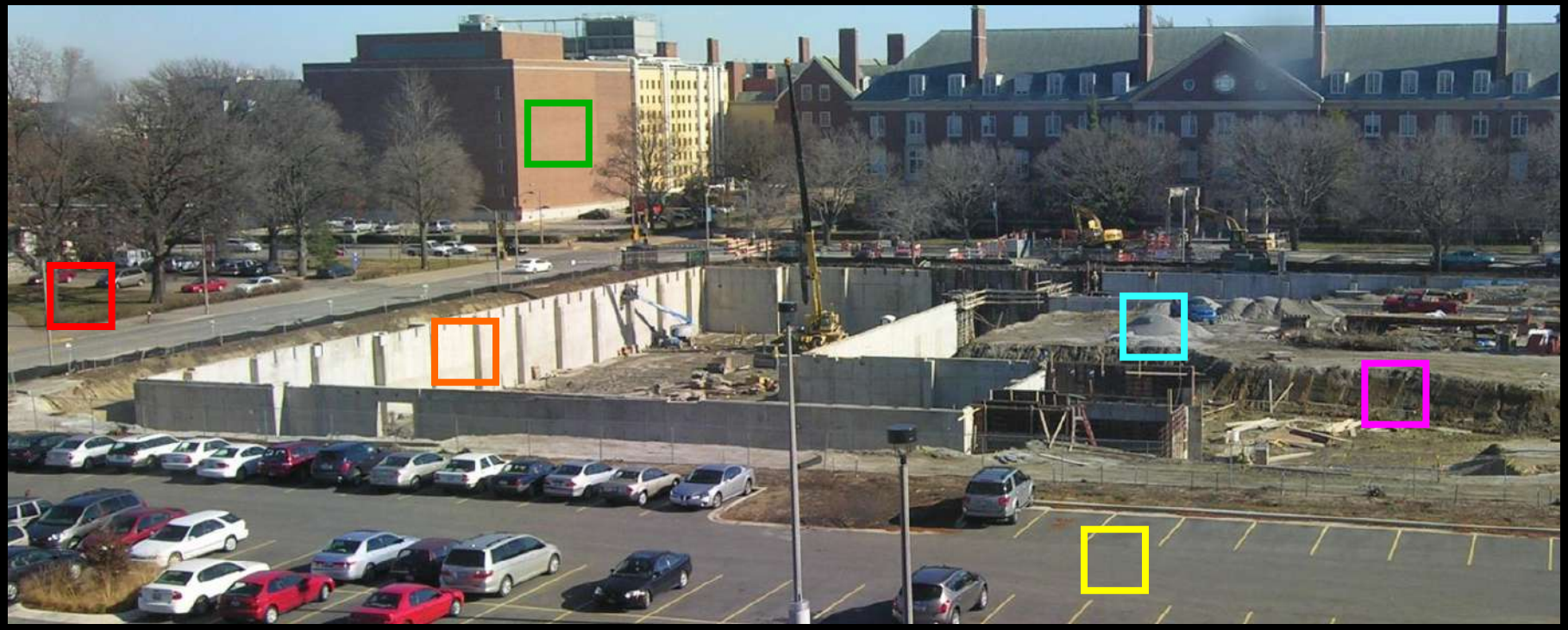
Geometry Informed Material Recognition

Joseph DeGol, Mani Golparvar-Fard, Derek Hoiem

CVPR 2016 (Spotlight Paper)

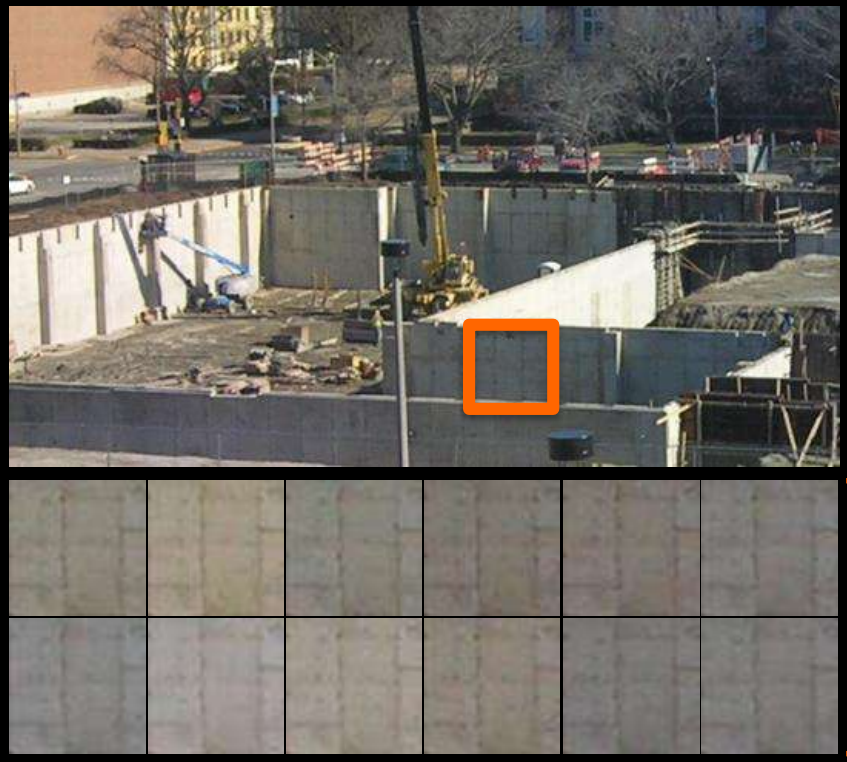
Recognize materials in real world scenes using images (2D) and geometry (3D).

Asphalt *Brick* *Concrete* *Grass* *Gravel* *Soil*



Challenges

Appearance changes due to lighting



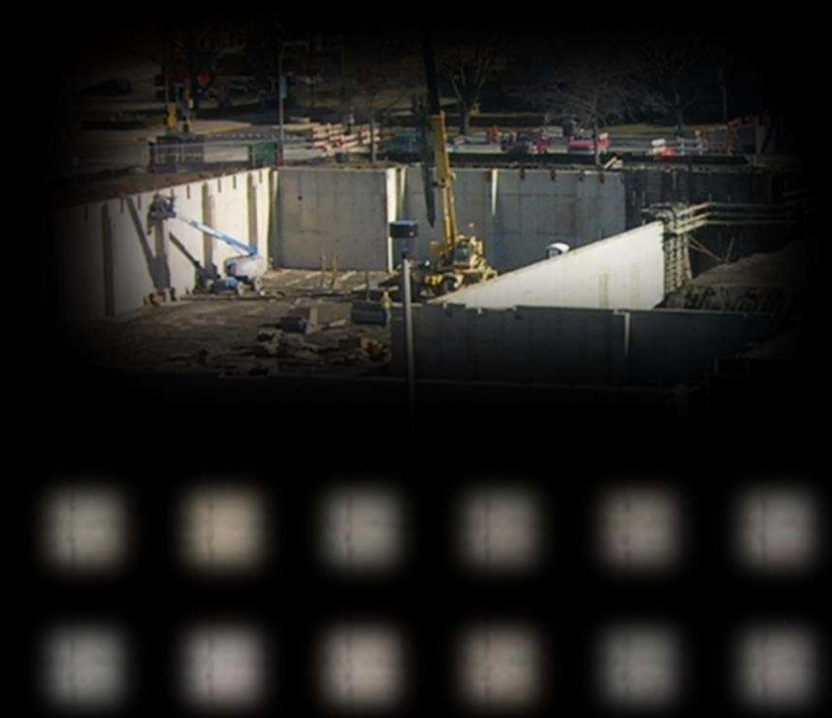
Challenges

Appearance changes due to lighting

Appearance changes due to perspective

Challenges

Appearance changes due to lighting



Appearance changes due to perspective

Appearance is similar within and across categories

Brick

Cement

Concrete

Soil

Geometry Aids Material Recognition

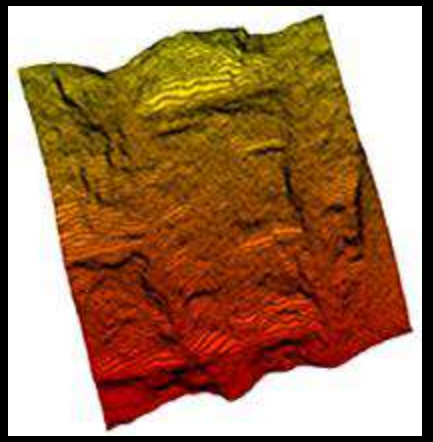
3D Geometry helps with categories with similar appearance but different geometry.

Paving

Stone - Limestone

Often confused with 2D

Correctly classified with 3D



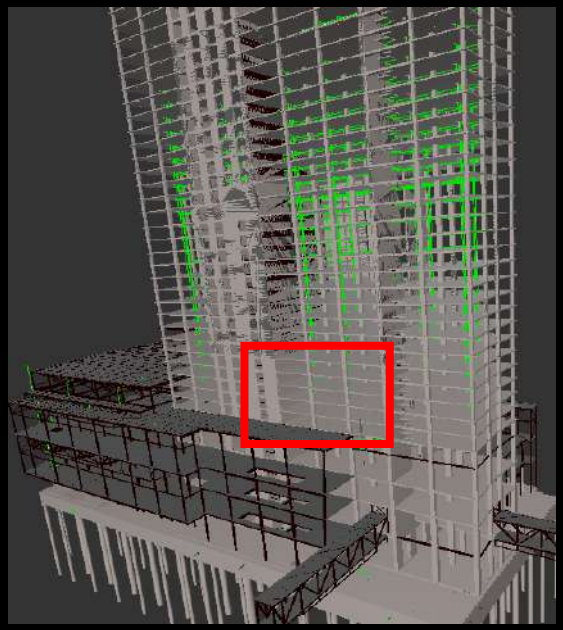
Best 2D (FV+CNN)	68.92
Best 3D (FV-N+CNN+N3D)	73.84

Geometry and Appearance Based Reasoning of Construction Progress Monitoring

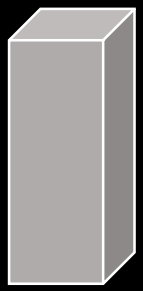
Kevin Han, Joseph DeGol, Mani Golparvar-Fard

ASCE Journal of Construction Engineering and Management

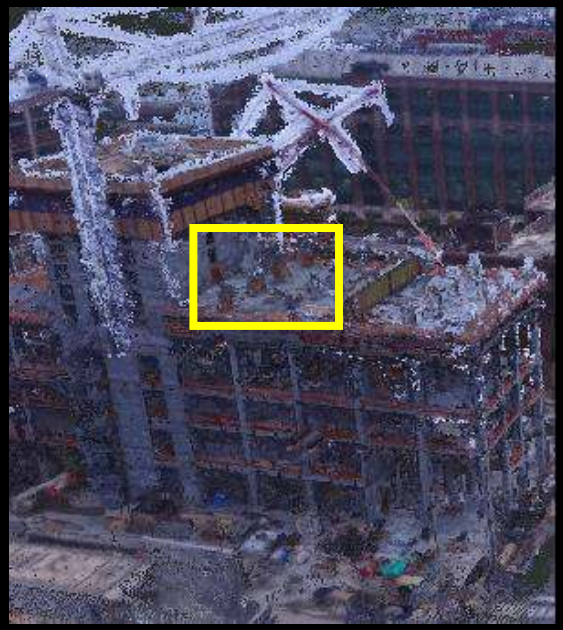
BIM



Cement Column



Week 24



Column : In Progress

Wood

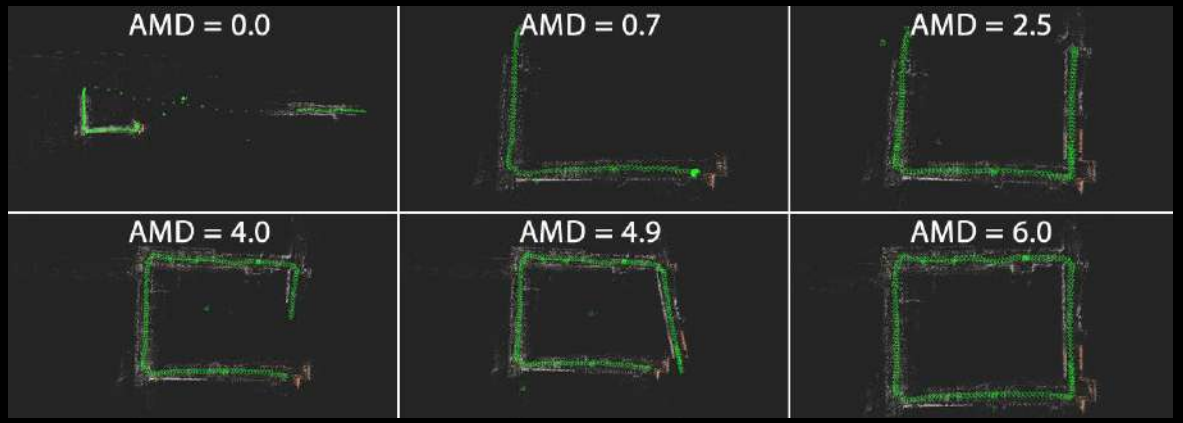
Week 29

Column : Complete

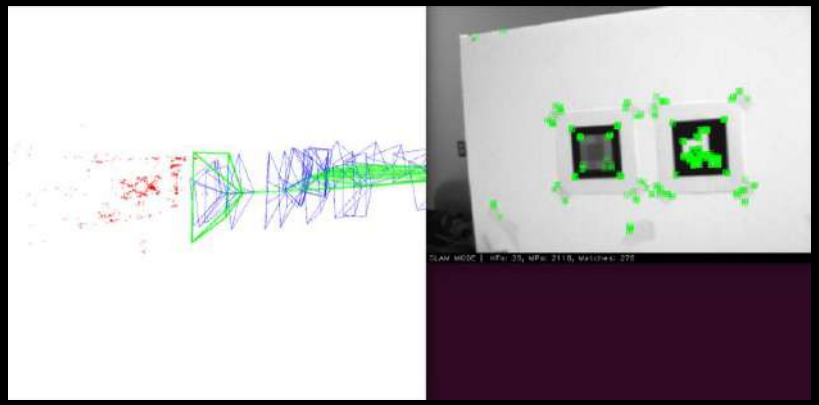
Cement

Conclusions / Future Work

- Placing the minimum number of markers that still results in successful 3D reconstructions
- Improving Matching and Resectioning without Markers



- Planning paths to improve 3D reconstruction
- Improved SLAM using Markers



Additional Work

Automatic Grasp Selection using a Camera in a Hand Prosthesis

Joseph DeGol, Aadeel Akhtar, Bhargava Manja, Timothy Bretl

EMBC 2016: Best Student Paper Award (3rd Place)

A Passive Mechanism for Relocating Payloads with a Quadrotor

Joseph DeGol, David Hanley, Navid Aghasadeghi, Timothy Bretl

IROS 2015

A Clustering Approach for Detecting Moving Objects Captured by a Moving Aerial Vehicle

Joseph DeGol, Myra Nam

ICASSP 2014

degol2.web.engr.illinois.edu/

Thanks and Questions

NDSEG Fellowship

3M Fellowship

F30HD084201

CMMI-1427111

CMMI-1544999

IIS-1320519

CMMI-1446765


Derek Hoiem


Tim Bretl


Mani Golparvar


Sudipta Sinha

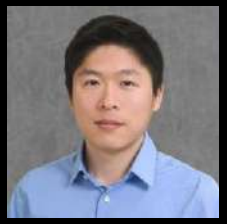

David Forsyth


Xinke Deng


Rajbir Kataria


Bhargava Manja


Aadeel Akhtar

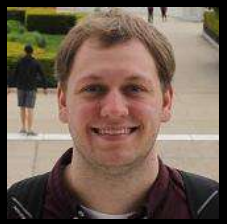

Kevin Han


Jae Yong Lee


Daniel Yuan


Myra Nam


Navid Aghasadeghi


David Hanley