

# Efficient Large-scale Photometric Reconstruction Using Divide-Recon-Fuse 3D Structure from Motion

Yueming Yang<sup>1</sup>, Ming-Ching Chang<sup>1,2</sup>, Longyin Wen<sup>1</sup>, Peter Tu<sup>2</sup>, Honggang Qi<sup>3</sup> and Siwei Lyu<sup>1</sup>

<sup>1</sup>State University of New York, Albany <sup>2</sup>GE Global Research <sup>3</sup>University of China Academy of Science

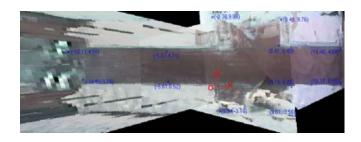
August 23-26, 2016 AVSS Colorado Springs, CO

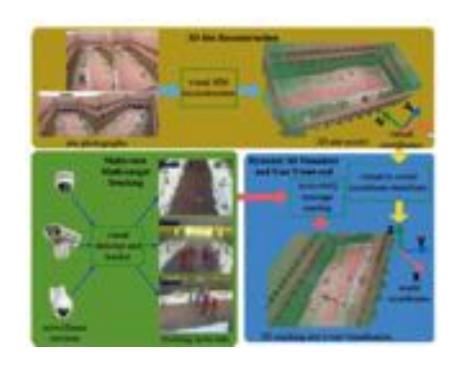
• 3D video surveillance



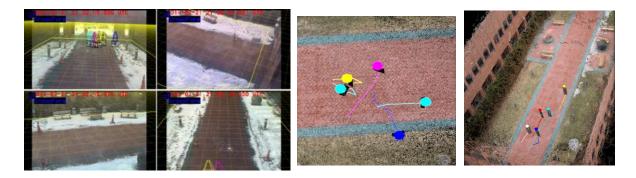
• 3D video surveillance







3D video surveillance





Yang, Chang, Lyu, Tu, ICIP 2015

3D video surveillance









Yang, Chang, Lyu, Tu, ICIP 2015

# **Research Trends on 3D Data Acquiring**

- Laser scanning
  - growing rapidly in recent years
  - but need expensive equipment



VISIDO IMAGING Inc. 2013

# Research Trends on 3D Data Acquiring

- Laser scanning
  - growing rapidly in recent years
  - but need expensive equipment

- Reconstruct from 2D images
  - popular research area in last decade
  - Computing is time consuming



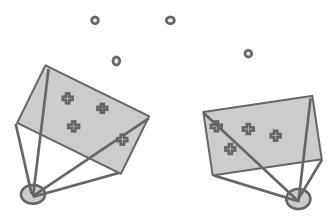
VISIDO IMAGING Inc. 2013



Agarwal, et.al., ICCV 2009

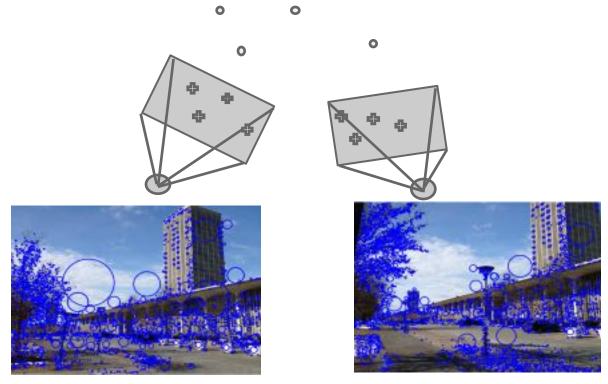
3D reconstruction from 2D images

Feature detection



3D reconstruction from 2D images

#### Feature detection

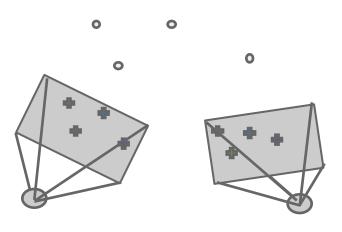


Detect features using SIFT [Lowe, IJCV 2004]

3D reconstruction from 2D images

Feature detection

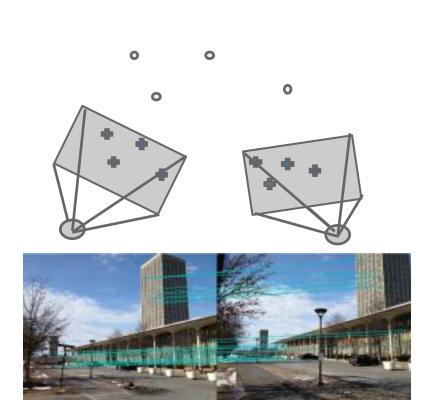
Feature matching



3D reconstruction from 2D images

Feature detection

Feature matching

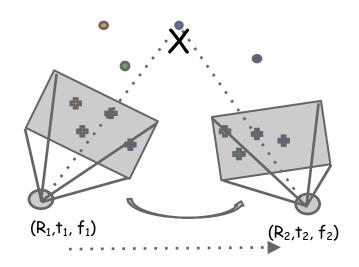


3D reconstruction from 2D images

Feature detection

Feature matching

Estimate 3D points



Wu, VisualSfM, 2011

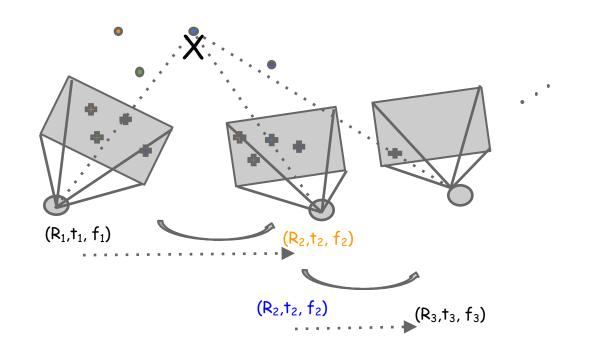
3D reconstruction from 2D images

Feature detection

Feature matching

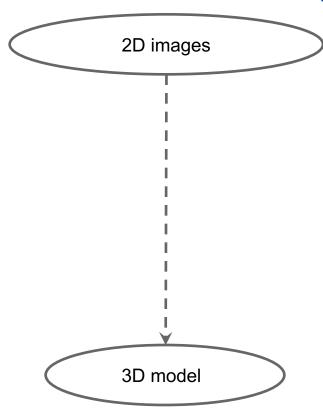
Estimate 3D points

Bundle adjustment



Wu, VisualSfM, 2011

#### 3D reconstruction from 2D images



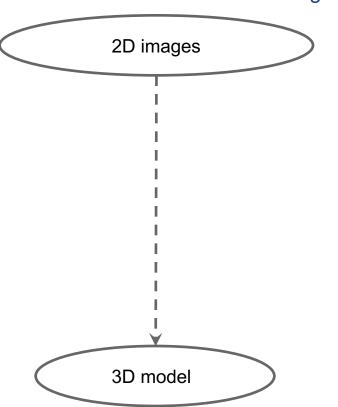
### problem: computing is time consuming

Data set	Images	Cores	Registered	Pairs verified	Pairs found	Time (hrs)		
						Matching	Skeletal sets	Reconstruction
Dubrovnik	57,845	352	11,868	2,658,264	498,982	5	- 31	16.5
Rome	150,000	496	36,658	8,825,256	2,712,301	13	1	
Venice	250,000	496	47,925	35,465,029	6,119,207	27	21.5	16.5

Table 1. Matching and reconstruction statistics for the three data sets.

Agarwal, et.al., ICCV 2009

3D reconstruction from 2D images



### problem: computing is time consuming

# Images	# Matches	#Matching time (seconds)
10	45	3.6
100	4950	396
1000	499500	39960
10000	49995000	3999600
100000	4999950000	399996000 (12.68 years)

### **Recent Trends**

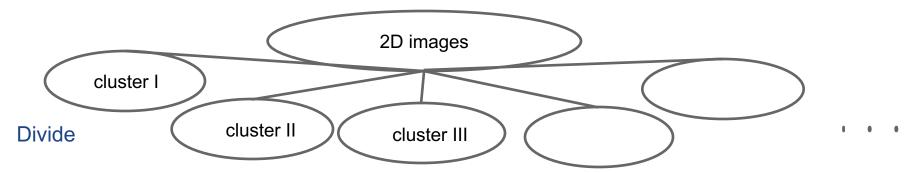
### Divide and Reconstruct

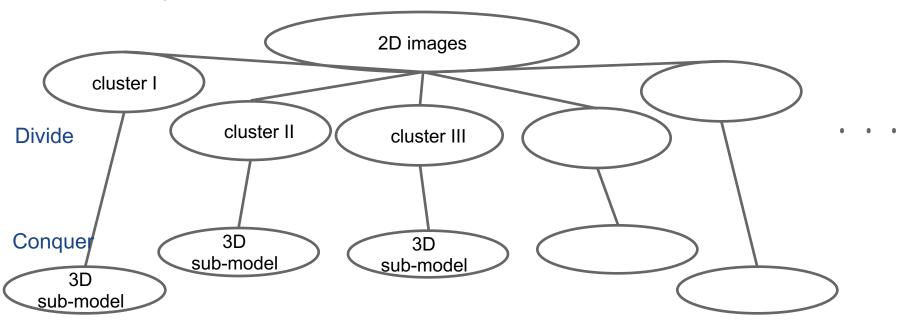


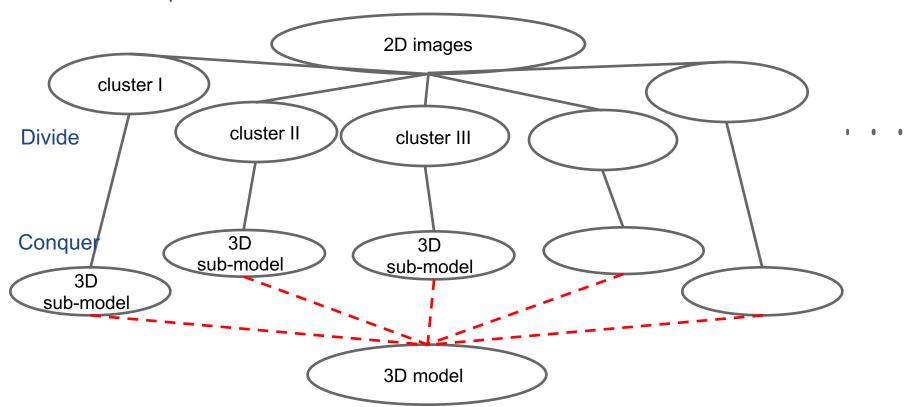
Yasutaka Furukawa, CVPR 2014

Divide and conquer then fusion

2D images







### **Recent Trends**

### Divide and Reconstruct



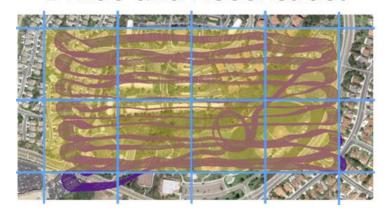
Yasutaka Furukawa, CVPR 2014



Bhowmick, et al., ACCV 2014

### **Recent Trends**

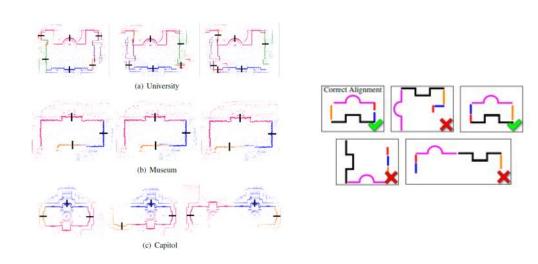
### Divide and Reconstruct



Yasutaka Furukawa, CVPR 2014



Bhowmick, et al., ACCV 2014



Cohen, et al., ICCV 2015

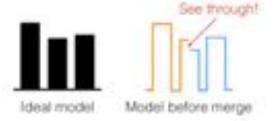
# Merge

- . The most difficult step
- Depends on the application (visualization, analysis, ...)

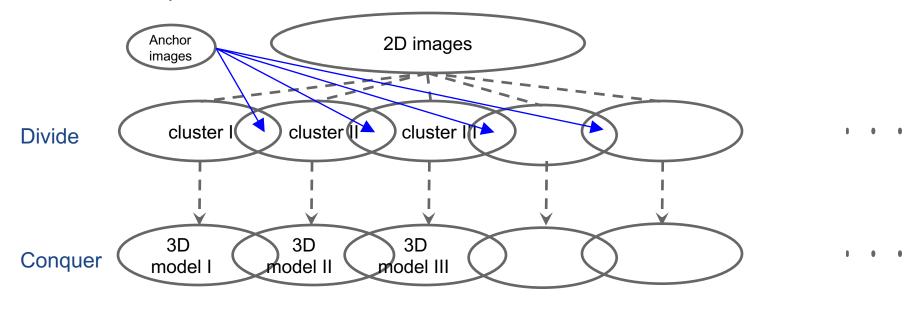


# Merge for visualization

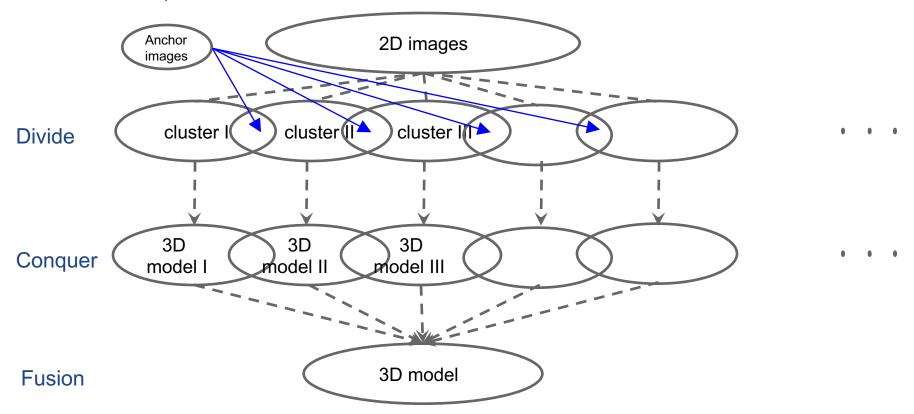
Hide gaps between reconstructions

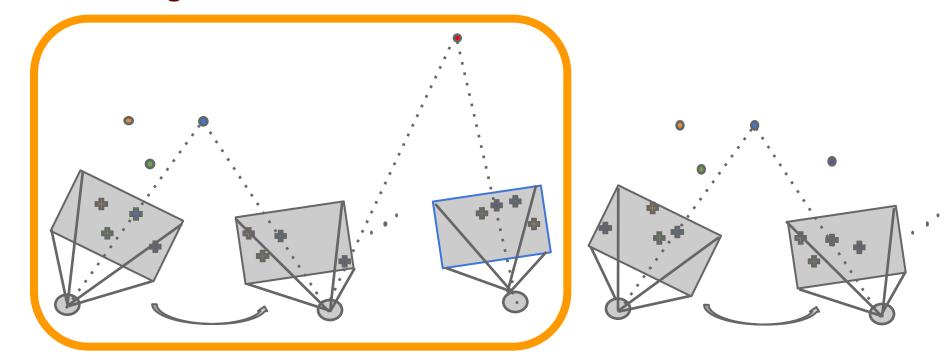


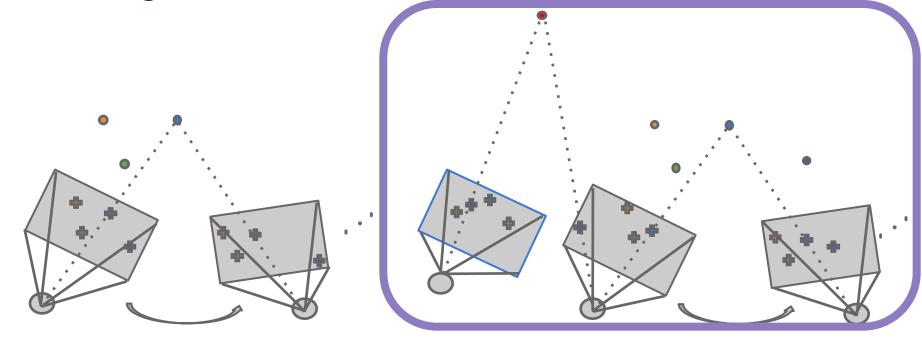
Yasutaka Furukawa, CVPR 2014

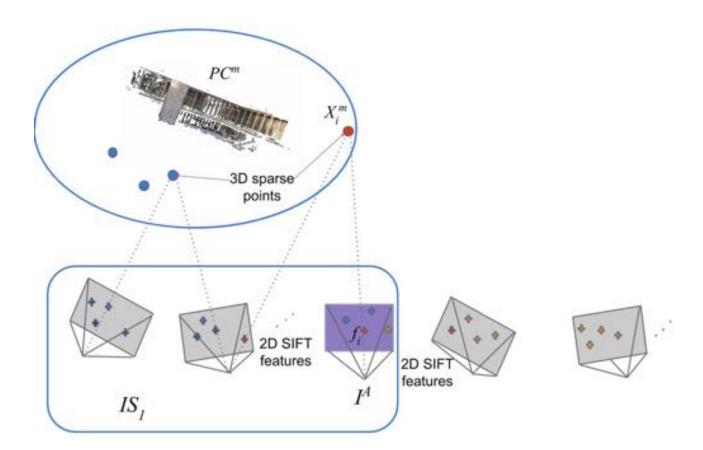


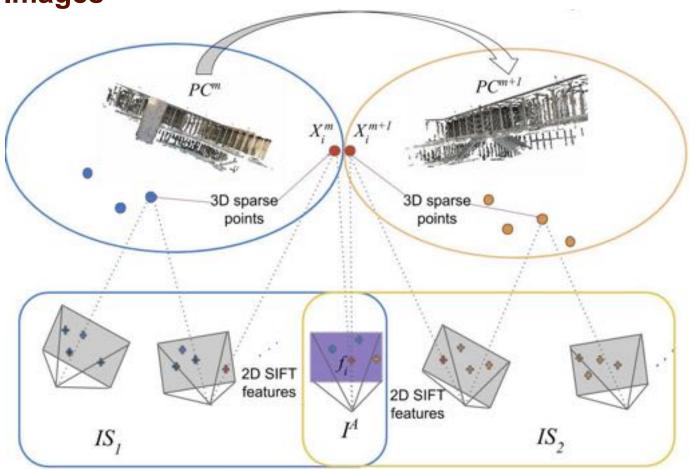


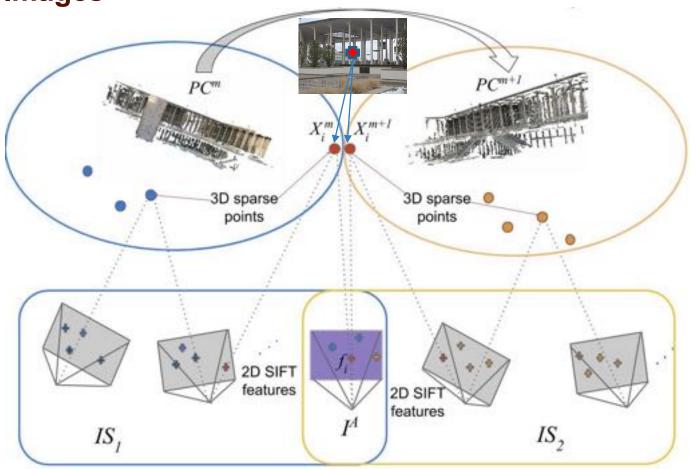




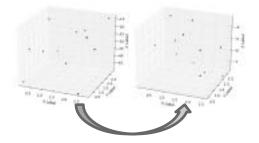








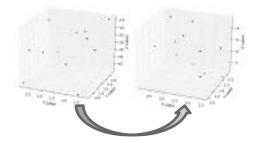
### Divide and conquer then fusion



Rigid transformation estimation

$$\vec{y_i} = \frac{1}{s} (R\vec{x_i} + \vec{c})$$

#### Divide and conquer then fusion

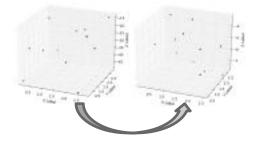


Rigid transformation estimation

$$\vec{y_i} = \frac{1}{s} (R\vec{x_i} + \vec{c})$$

$$\min_{R,s,\vec{c}} \sum_{i=1}^{n} \|s\vec{y_i} - R\vec{x_i} - \vec{c}\|^2 \quad \text{s.t.} \quad R^T R = R R^T = I. \quad (1)$$

#### Divide and conquer then fusion



Rigid transformation estimation

$$\vec{y_i} = \frac{1}{s} (R\vec{x_i} + \vec{c})$$

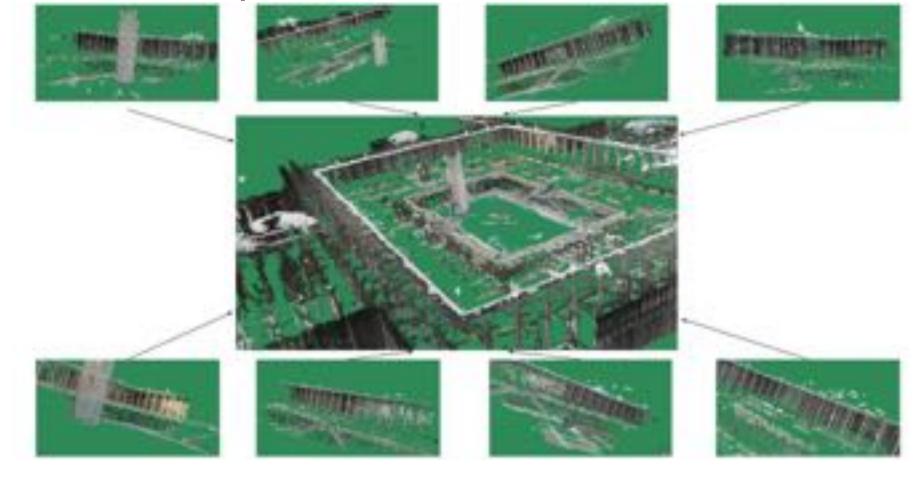
```
\min_{R,s,\vec{c}} \sum_{i=1}^{n} \|s\vec{y_i} - R\vec{x_i} - \vec{c}\|^2 \quad \text{s.t.} \quad R^T R = R R^T = I. \quad (1)
```

```
Table 1. Procedure EstTransformRANS&C(X, Y, K)

    index +- (1 to n)

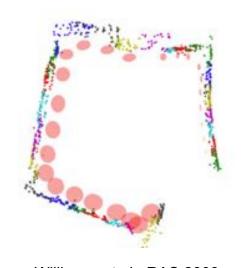
 2: n_inliers e= 0
    for k = 1 to K do.
         ide wrandomly select 6 numbers from index
         X_i \leftarrow X(sdx), Y_i \leftarrow Y(sdx)
         R_i, s_i, c_i \leftarrow EstTransformSVD(X_i, Y_i)
         x_i \leftarrow [s_i \mathbf{Y}_i - \mathbf{R}_i \mathbf{X}_i - \ell_i]
         n_s \leftarrow number of items in \epsilon_s which are \leq \tau
         if n, \ge minfers then
              n_inbers \leftarrow n_i
              \mathbf{R} s.c.e \leftarrow \mathbf{R} s.c.c.e.
    end for
14: return R. s. c. c. n. in/irrs
```

Robust rigid transformation estimation

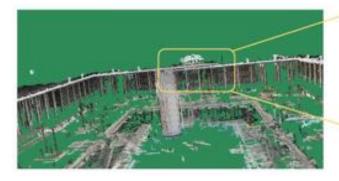


Comparison of computational time for the two university campus datasets

Dataset	Clusters	#Images	#Anchors	Match pairs	Matching time	SfM (BA)
Campus Podium	Cluster 1	201	C1-C2: 14	20100	0.43 hours	55 seconds
	Cluster 2	188	C1-C2; 7	17,578	0.4 hours	45 seconds
	Cluster 3	147	C1-C2: 20	30,576	0.23 hours	35 seconds
	Cluster 4	215	C1-C2: 11	23,005	0.51 hours	42 seconds
	Cluster 5	218	C1-C2: 13	23,653	0.48 hours	57 seconds
	Cluster 6	260	C1-C2: 17	33,670	0.70 hours	80 seconds
	Cluster 7	258	C1-C2:19	33,153	0.73 hours	62 seconds
	Cluster 8	293	C1-C2: 10	42,778	0.9 hours	62 seconds
	Divide-conquer	1780	111	224,513	4.38 hours	438 seconds
	All(Brute force)	1,669		139,1946	26.80 hours	512 seconds
Track Field	Cluster 1	461	C1-C2: 11	106,030	1.84 hours	191 seconds
	Cluster 2	466	C2-C3: 9	10,8345	2.13 hours	170 seconds
	Cluster 3	415	C3-C4: 10	85,905	1.71 hours	91 seconds
	Cluster 4	359	C4-C5: 10	64,261	1.41 hours	103 seconds
	Cluster 5	290	C5-C6: 10	41,905	0.78 hours	77 seconds
	Cluster 6	276	C6-C7: 10	37,950	0.59 hours	106 seconds
	Cluster 7	272	C7-C8: 10	36,856	0.73 hours	166 seconds
	Cluster 8	311	C8-C1: 11	48,205	0.97 hours	130 seconds
	Divide-conquer	2,850	81	156,550	10.16 hours	1,034 second
	All(Brute force)	2,769	0000	3,832,296	67.67 hours	887 seconds



Williams, et.al., RAS 2009



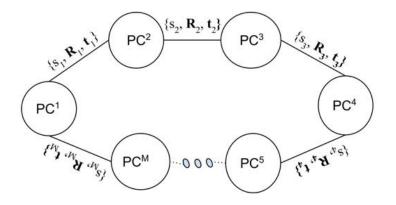




Williams, et.al., RAS 2009





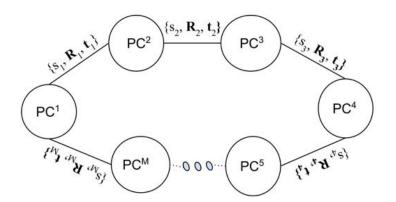




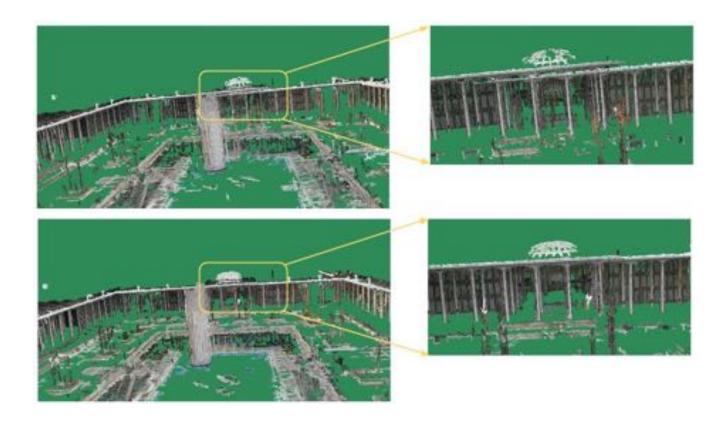
Williams, et.al., RAS 2009







$$X^1 = \mathbf{R}_M \dots \mathbf{R}_3(\mathbf{R}_2(\mathbf{R}_1\mathbf{X}^1 + \mathbf{t}_1) + \mathbf{t}_2) + \mathbf{t}_3) \dots + \mathbf{t}_M$$



# **Other Experiments**









# **Other Experiments**

















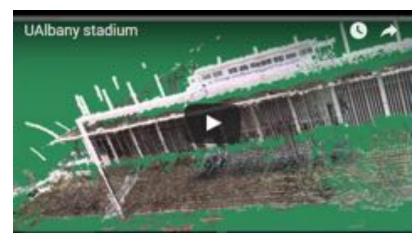




# **Video Demo**







### **Conclusions**

Provide a way of turning video surveillance into 3D

- Largely reduce the image matching time compare to traditional SfM 3D reconstruction
- Propose a novel formulation of adding "anchor images" to provides powerful hints in the stitching individual 3D reconstructions

### **Future works**

- Improve the avatar figure in 3D surveillance
- Dense SIFT features
- Digitize the world and make 3D tour applications

# Thank you!