Dynamic SfM

Detecting Scene ***Changes*** from Image Pairs

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Niloy J. Mitra, University College London

Problem Statement

- Estimate Structure and Motion from a pair of uncalibrated images

Input： two RGB images with the scene changed

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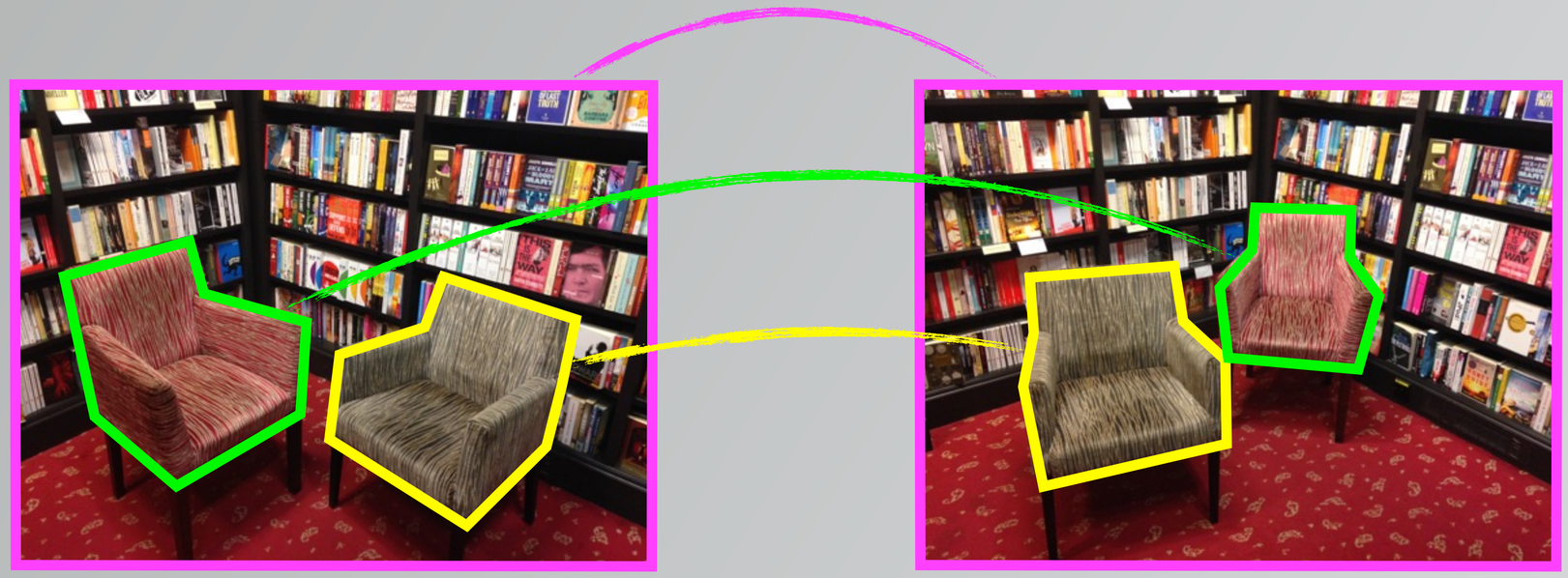

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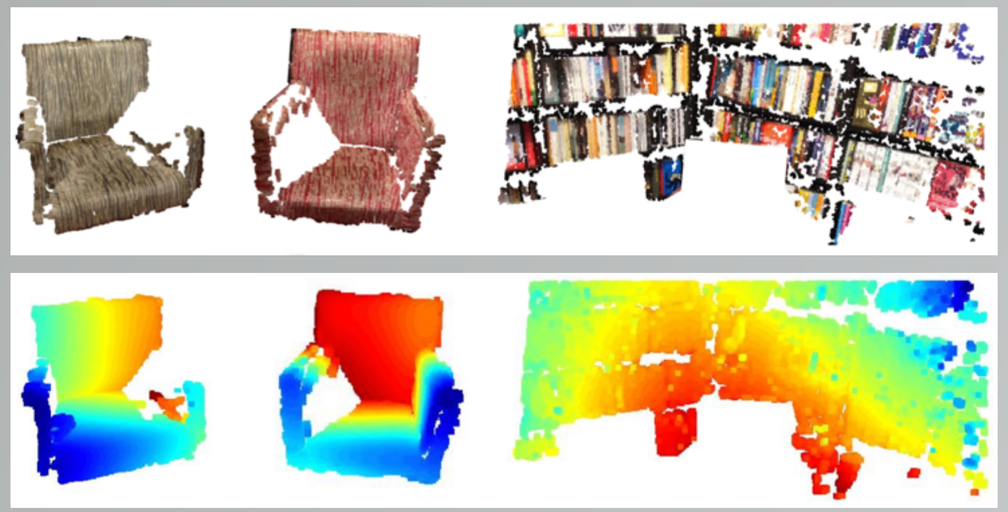

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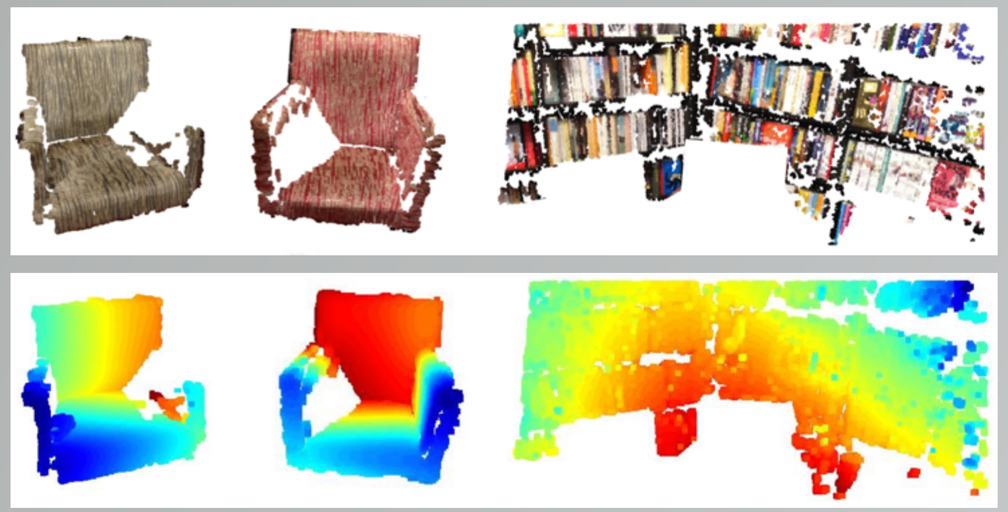

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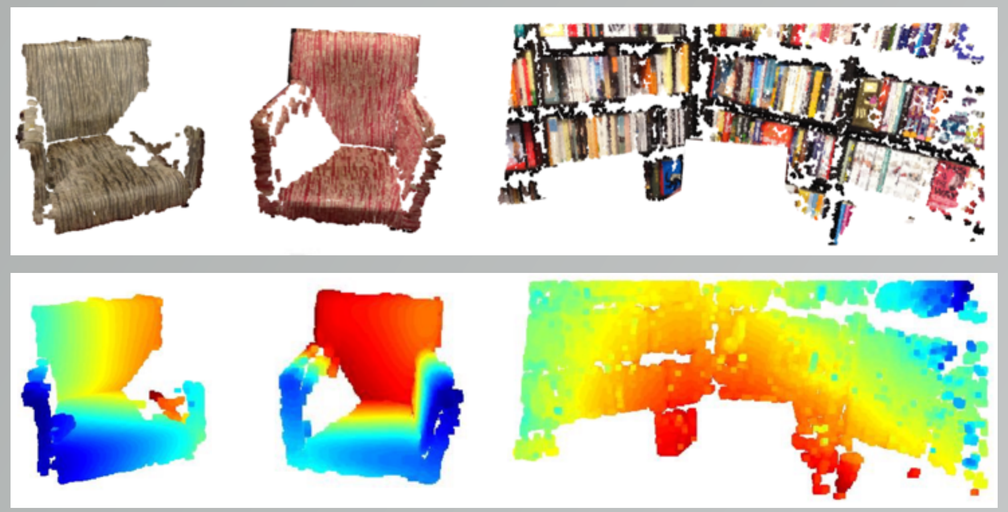
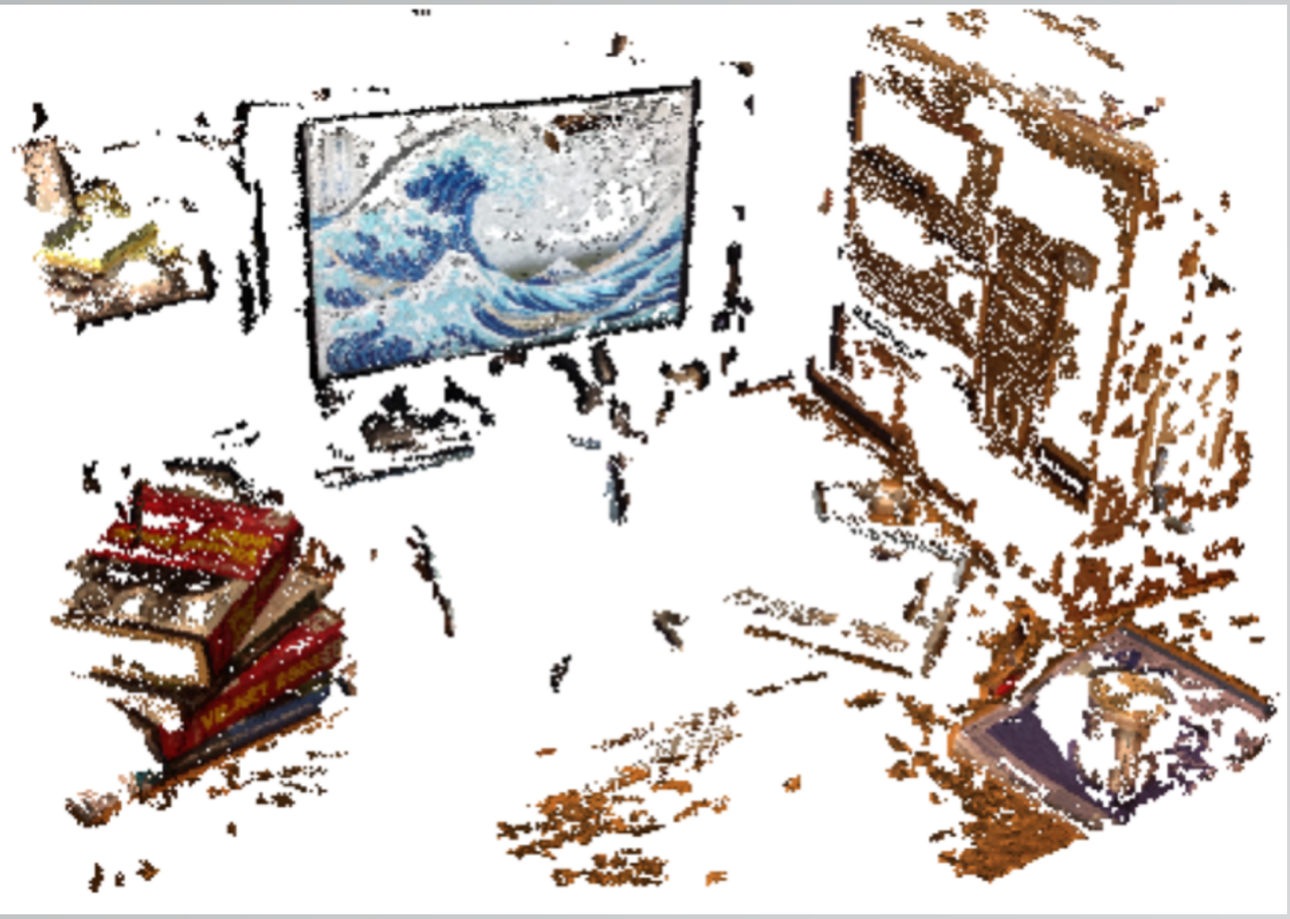


Direct Solution



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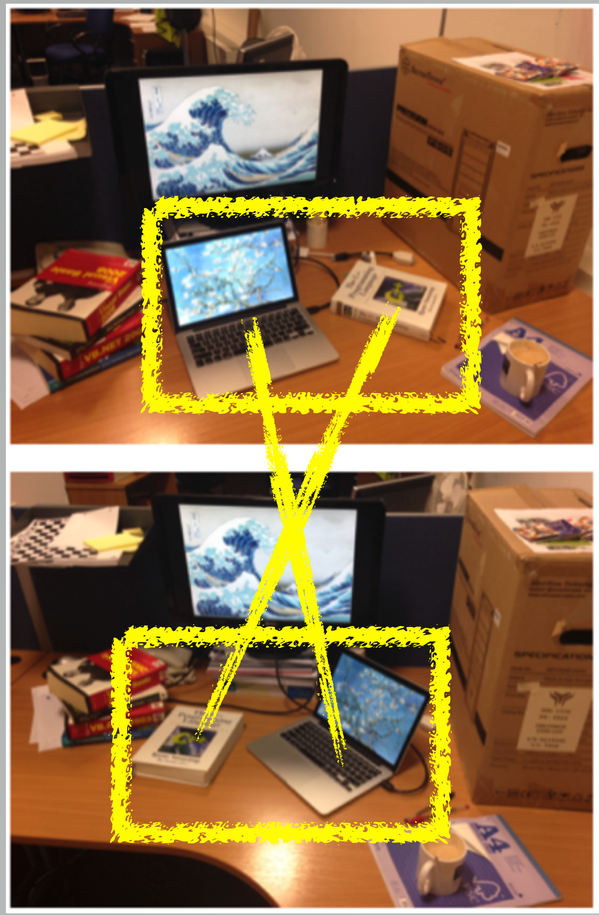
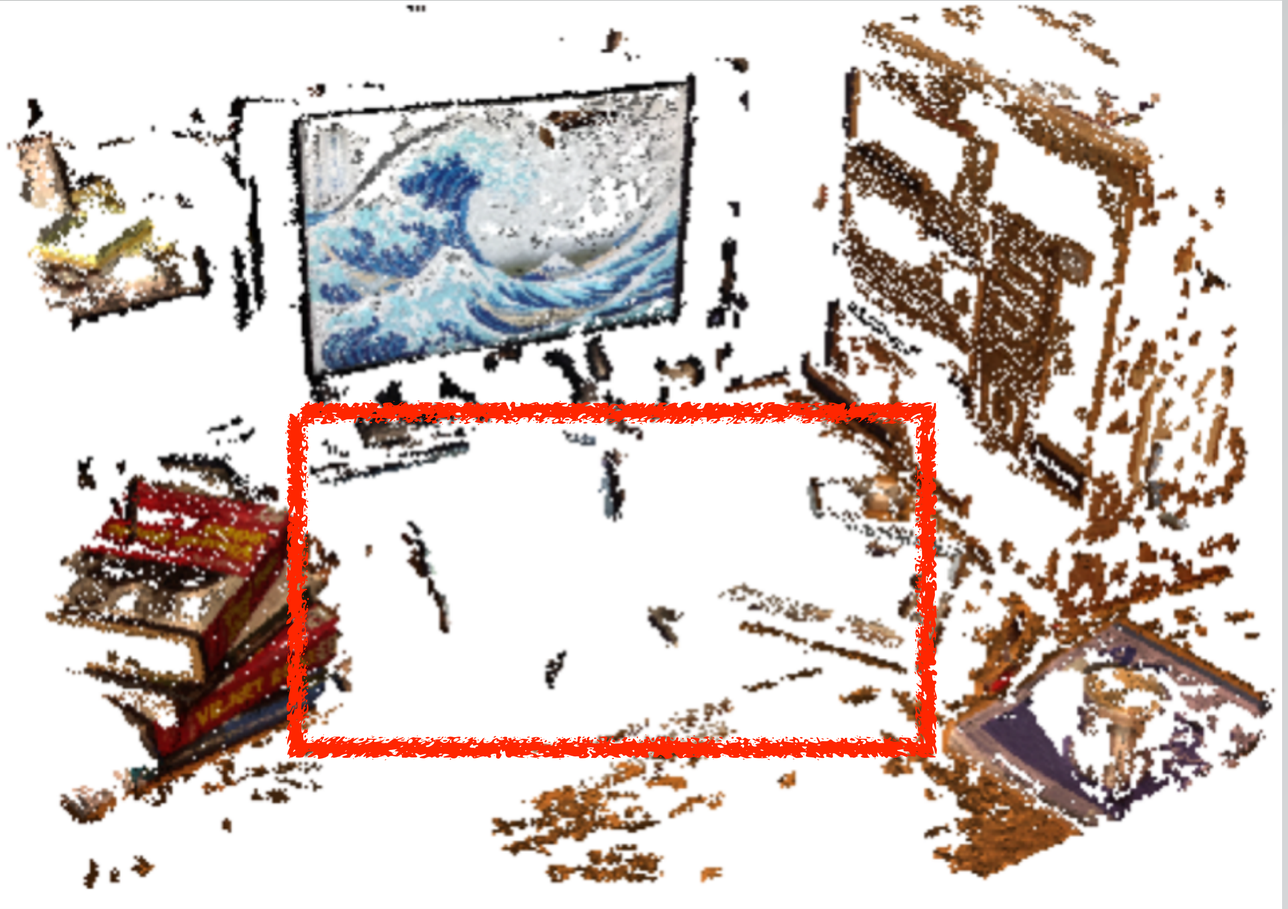
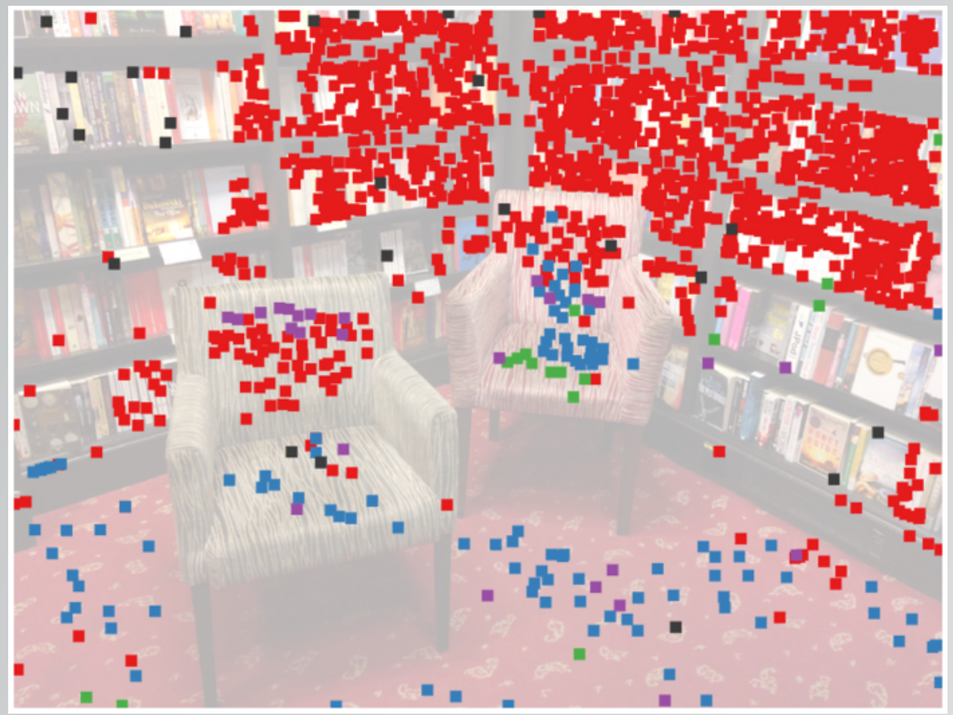




Combined Solution?

- Motion Segmentation
  - GPCA [VH04, YRM06, RTVM10]
  - Video based: [OSVG10], [JPS14], [RRGA12]
  - **PEARL** [IB12, DOIB12] *(state of the art)*



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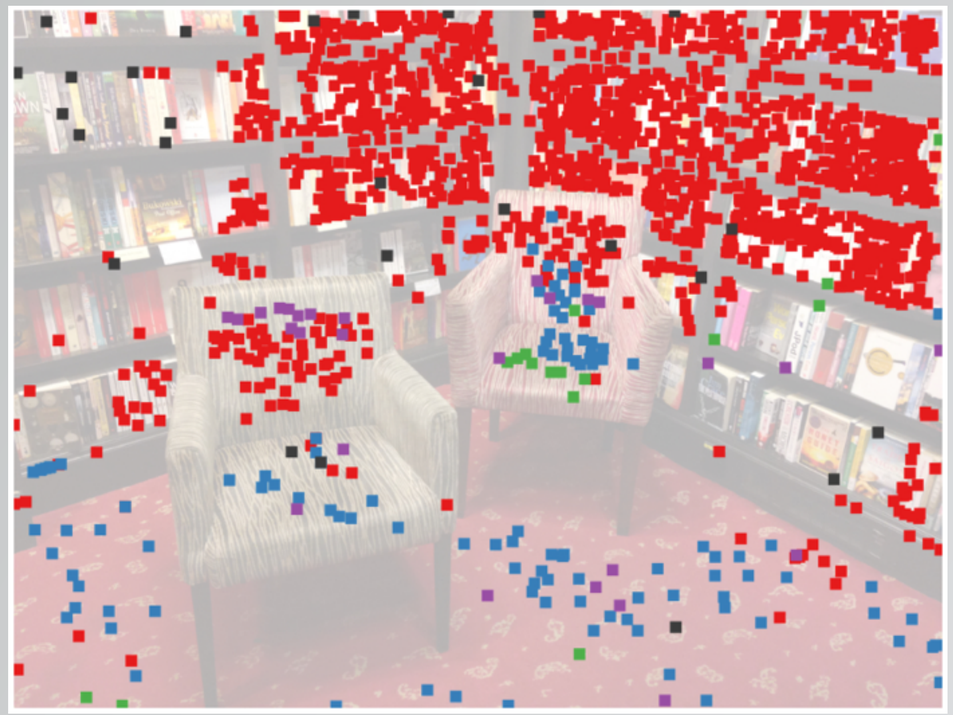
- Structure Estimation
  - **Structure from Motion** (SfM) [Wu11]
- Dense Reconstruction
  - **CMVS/PMVS** [FP10]
  - CMPMVS [JP11]
  - MVE [SFG14]
  - …



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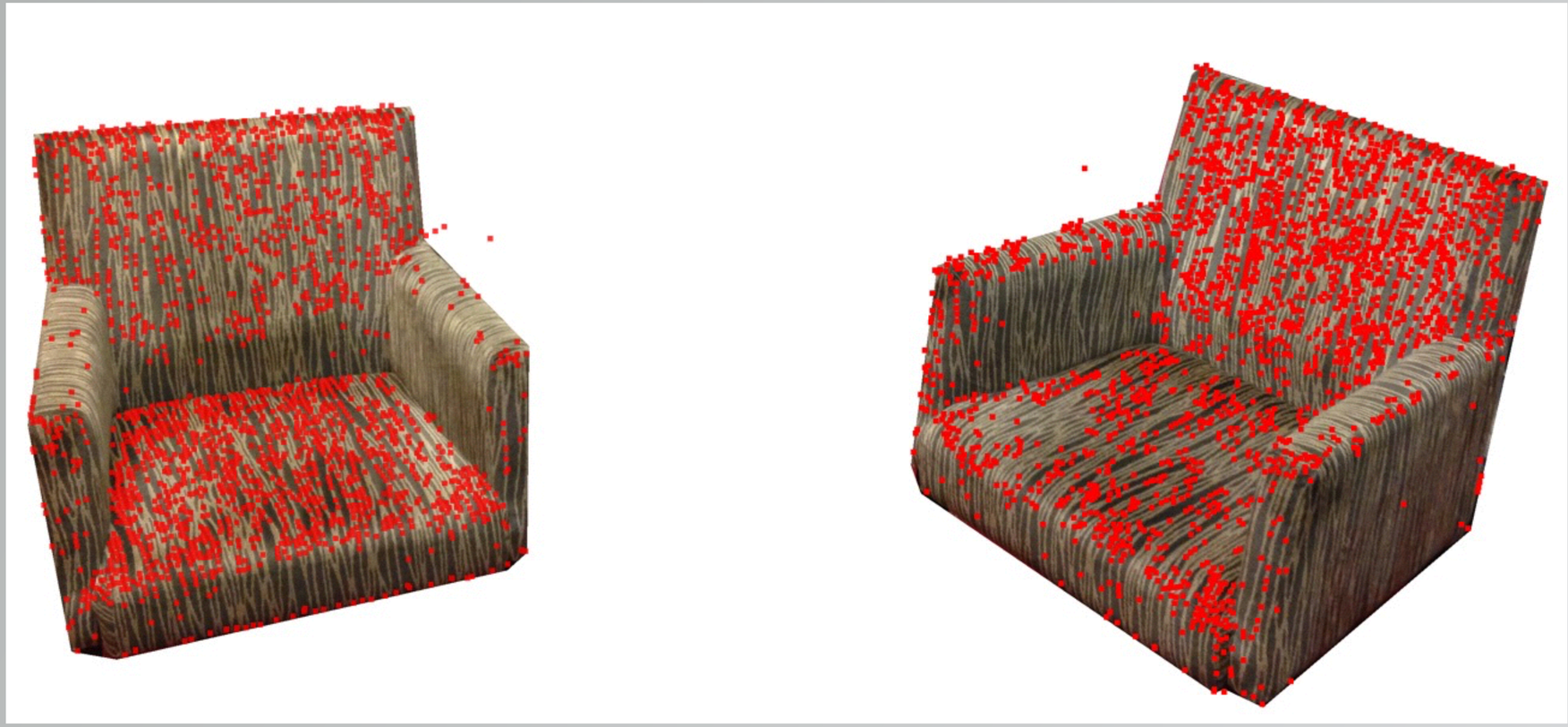

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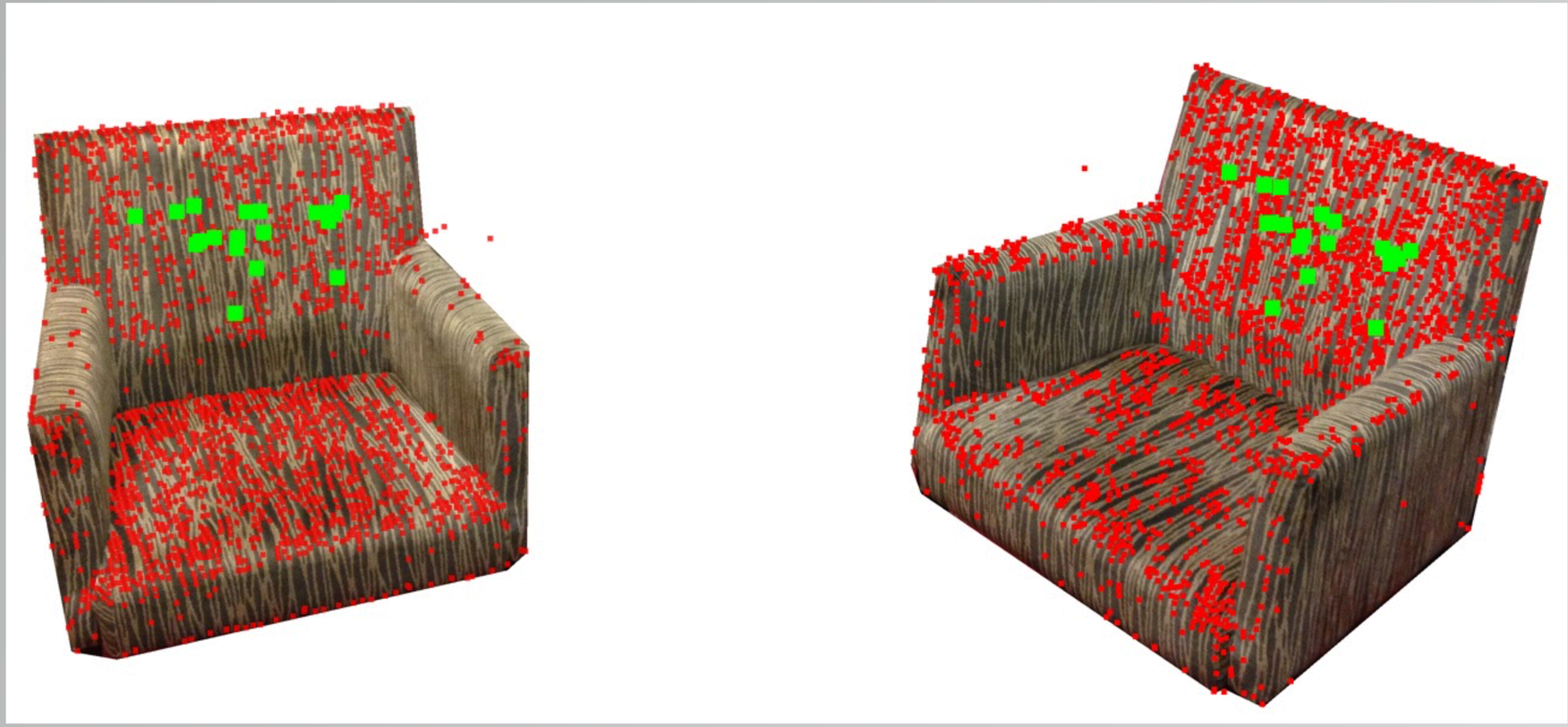

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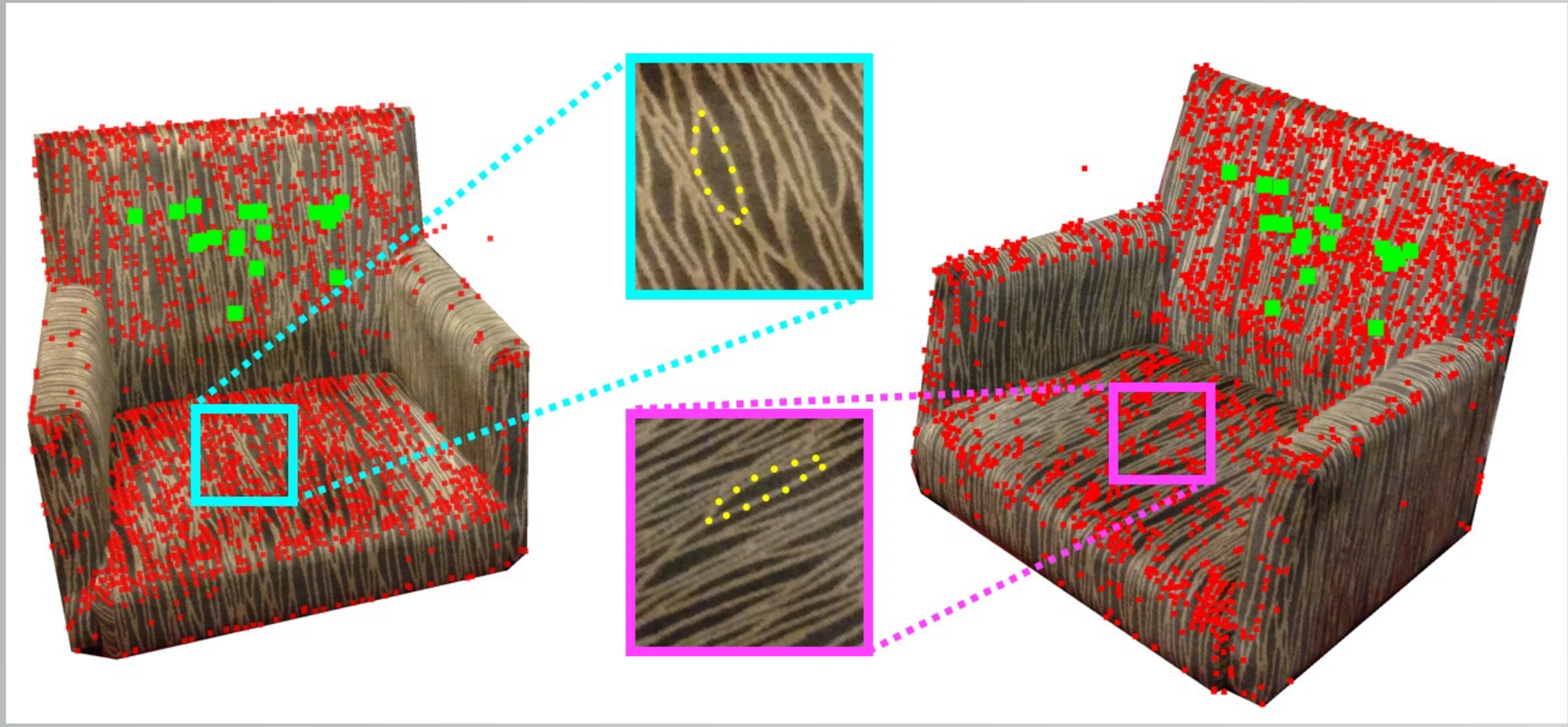

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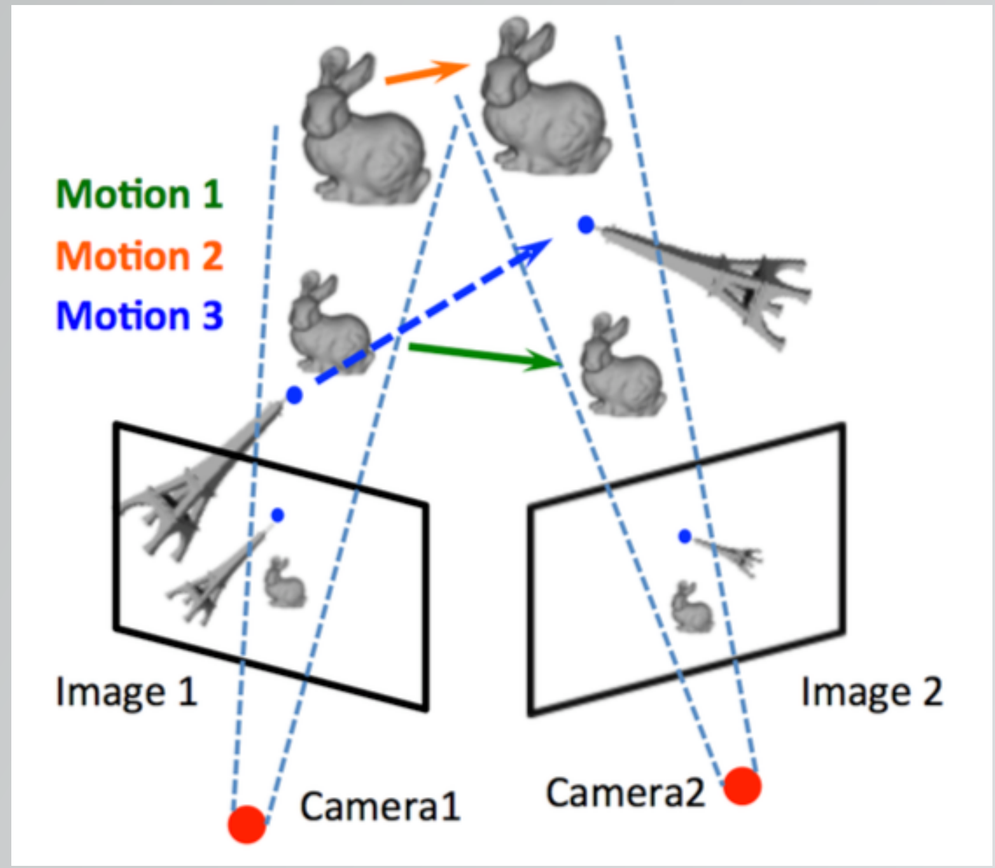
  - Initialize the optimization
  - two-view ambiguity



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- Generate denser 3D point cloud

Dynamic SfM

Input

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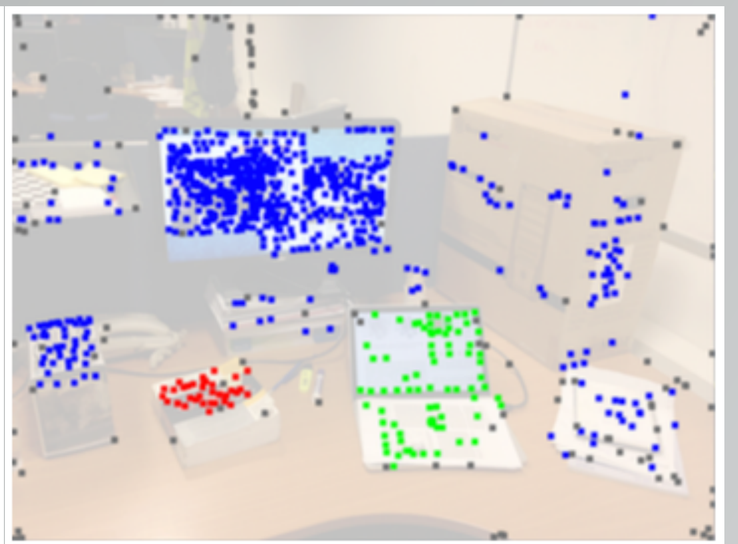
Pre-boosting
generate correspondence

Dynamic SfM



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continuous optimization
correspondence grouping

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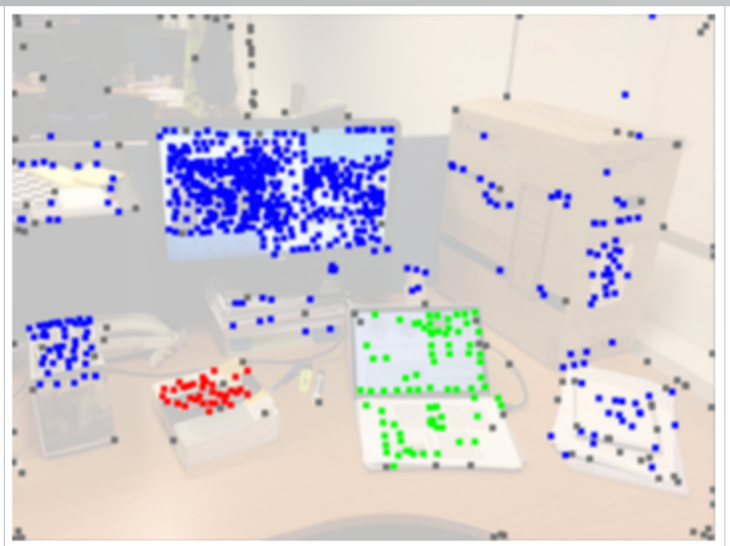

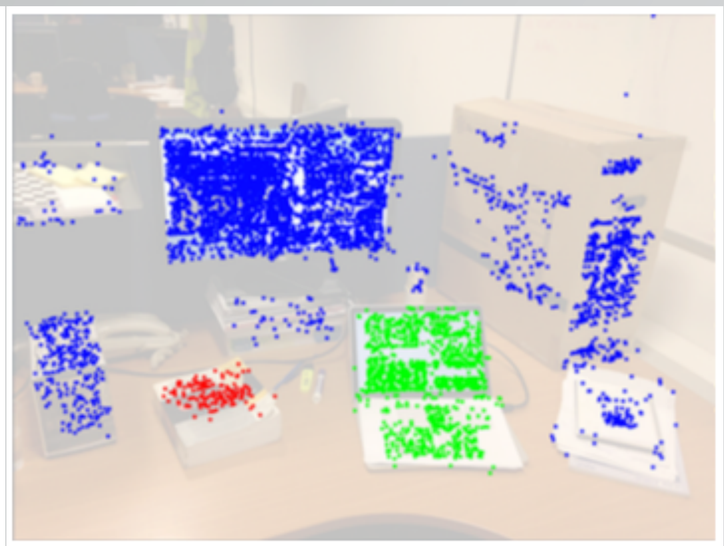

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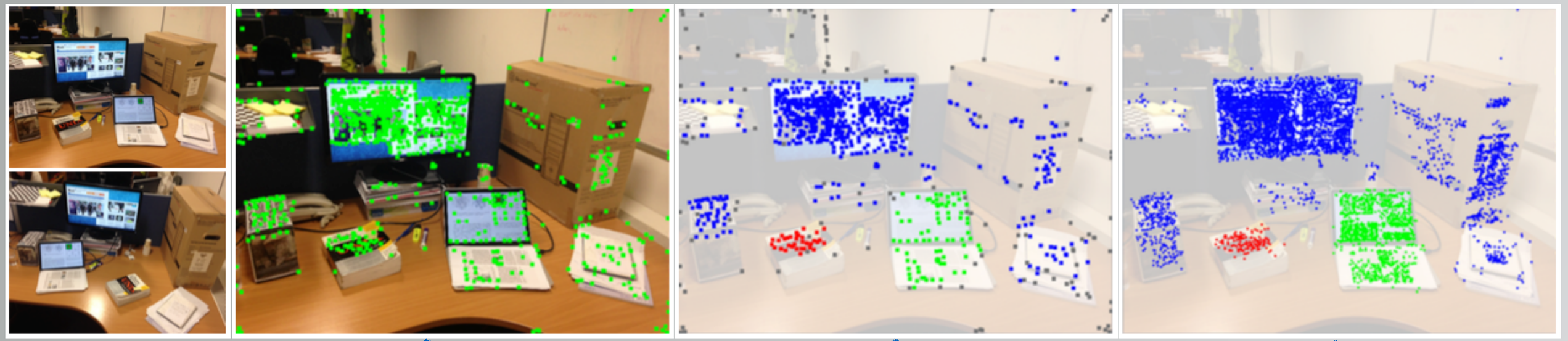

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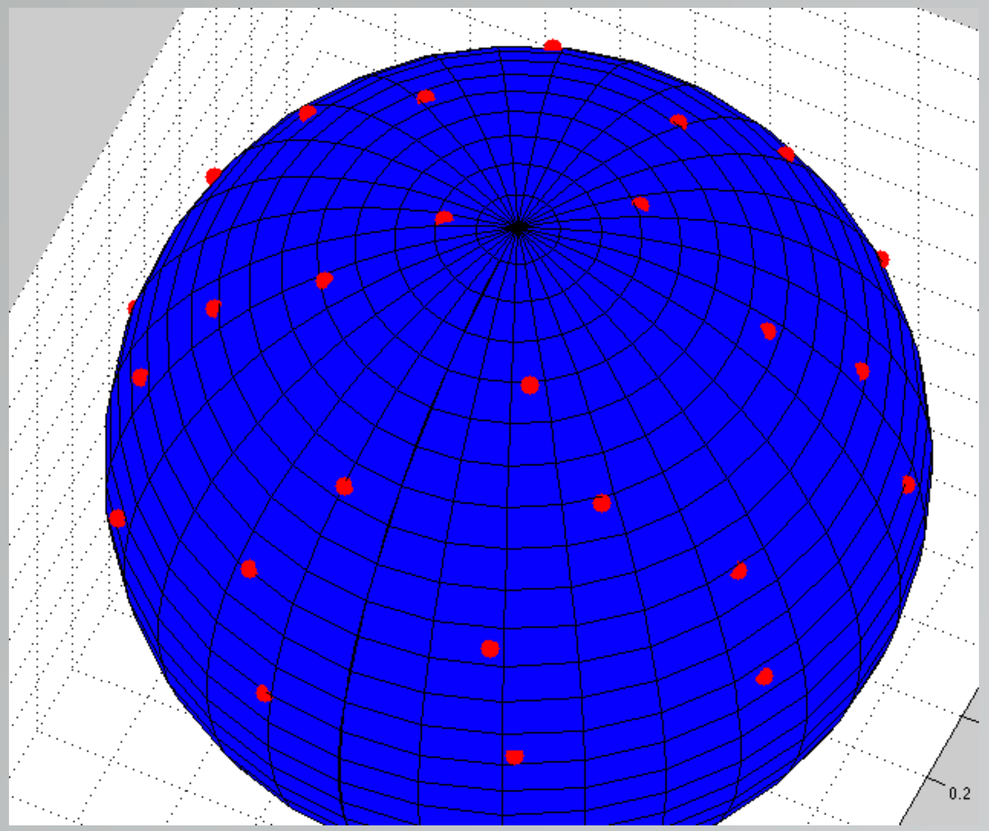

$$u_i = \arcsin\left(1 - \frac{2i-1}{2S}\right) \qquad v_i = u_i\sqrt{2\pi S}$$

$$\mathbf{n}_i = [\cos(u_i)\cos(v_i);\ \cos(u_i)\sin(v_i);\ \sin(u_i)]$$

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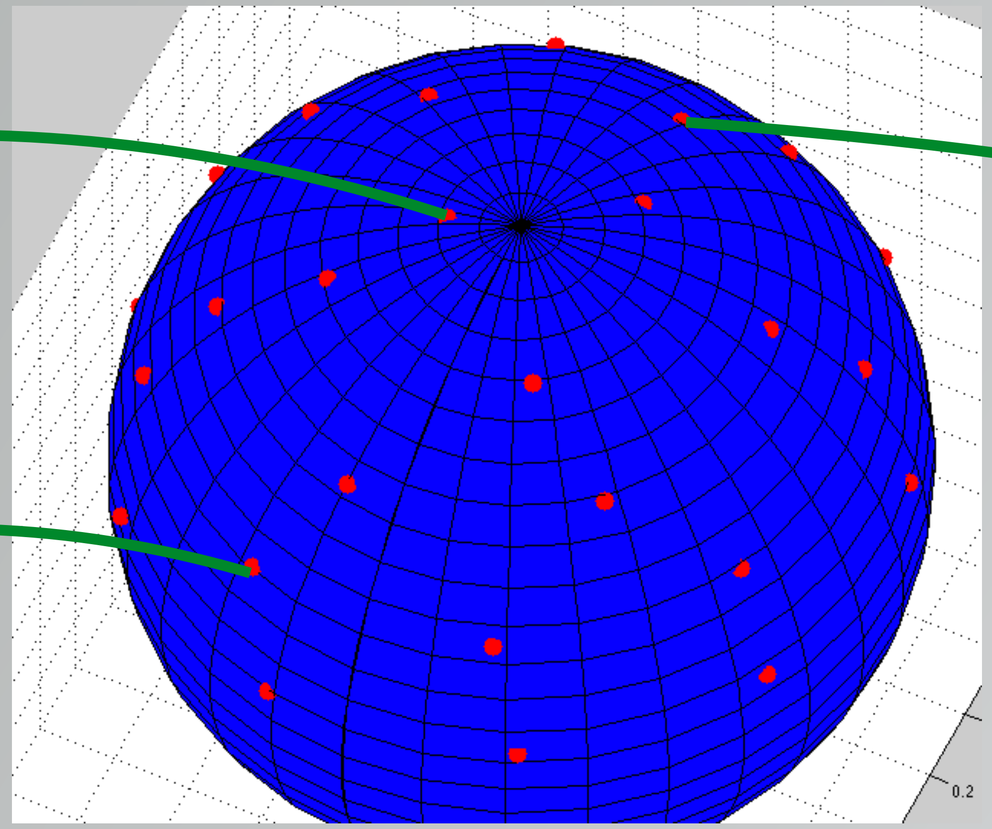

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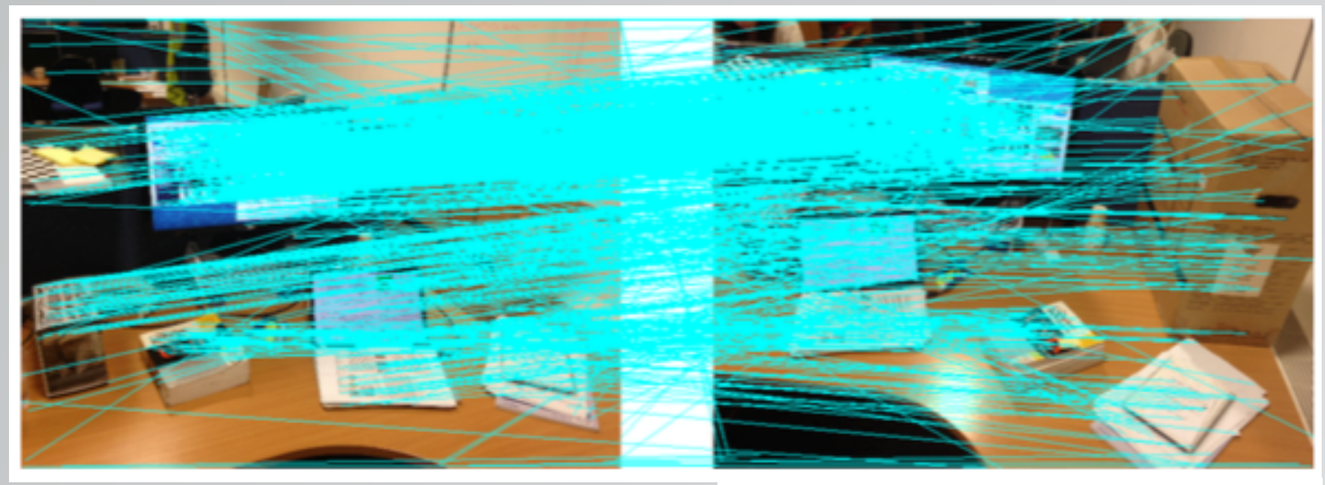
Original match



After Pre-boosting

Continuous Optimization

Motion candidates
Camera parameters

3D positions

Group label

$$E(\{L_i\}, \{\mathbf{d}_k\}, \{\alpha^k\}) :=$$

$$E_{data} + E_{complexity} + E_{outlier} + E_{consistency}$$

Date term	lower reprojection error
Complexity term	penalizes having too many separate groups to describe the motions
Outlier term	avoid trivial solution of all outliers
Consistency term	regularizes false positive matches cause by two-view ambiguity

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$$\sum_{i=1}^{M} \alpha_i^k \leq 1 \quad \forall k$$

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$$\sum_{i=1}^{M} \alpha_i^k \leq 1 \quad \forall k$$

$$E_{data}(\{L_i\},\{\mathbf{d}_k\},\{\alpha^k\}) = \sum_{k=1}^{N}\sum_{i=1}^{M} \alpha_i^k \| \mathbf{d}_k \|_{L_i}$$

$$E_{complexity}(\alpha) = \omega_1 \cdot \sum_{i=1}^{M} \left(\sum_{k=1}^{N} \alpha_i^k \right)^{\beta}$$

$$E_{outlier}(\alpha) = \omega_2 \cdot \left(\sum_{k=1}^{N} \delta_k \left(1 - \sum_{i=1}^{M} \alpha_i^k \right) \right)$$

$$E_{consistency}(\alpha) = \omega_3 \cdot \sum_{(p,q)\in DN} \theta_{p,q} \| \alpha^p - \alpha^q \|$$

Optimization initialization
with **Domain problem**

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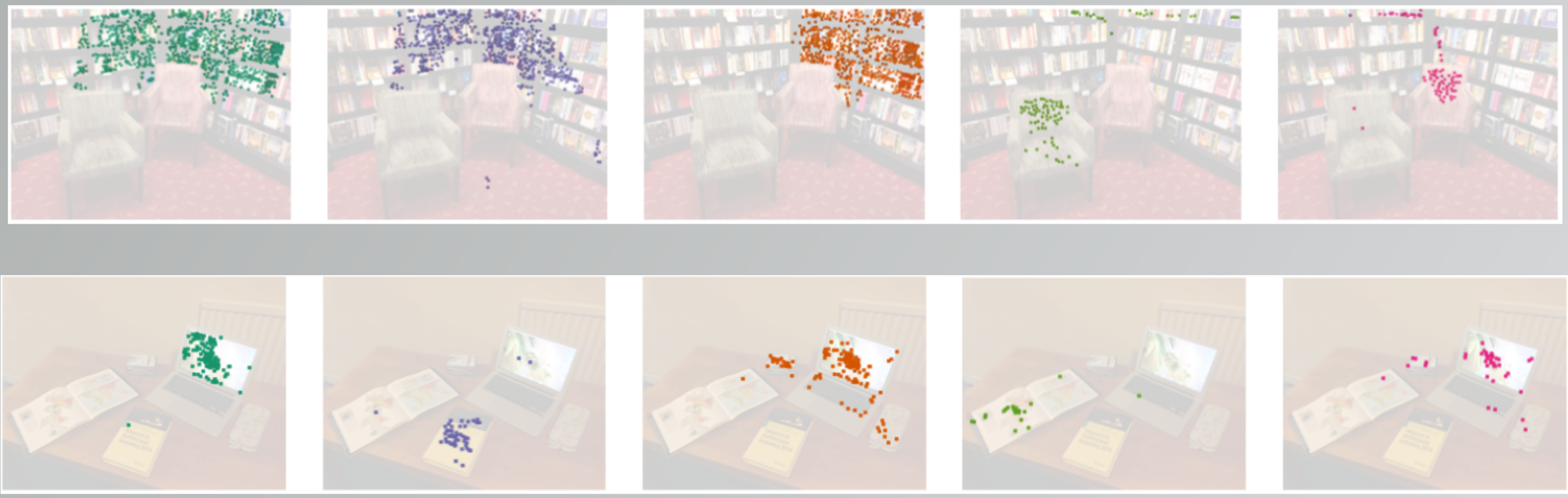
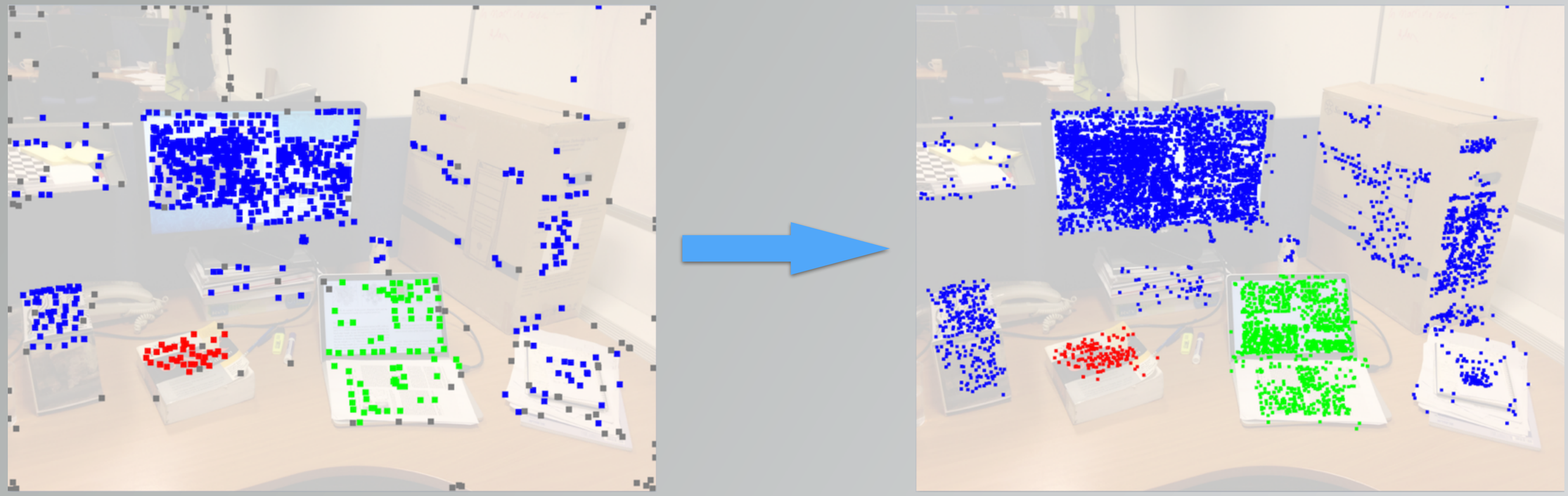
RANSAC ⟶ ***Reweighted*** **RANSAC**



Post-boosting

Patch based correspondence establishing



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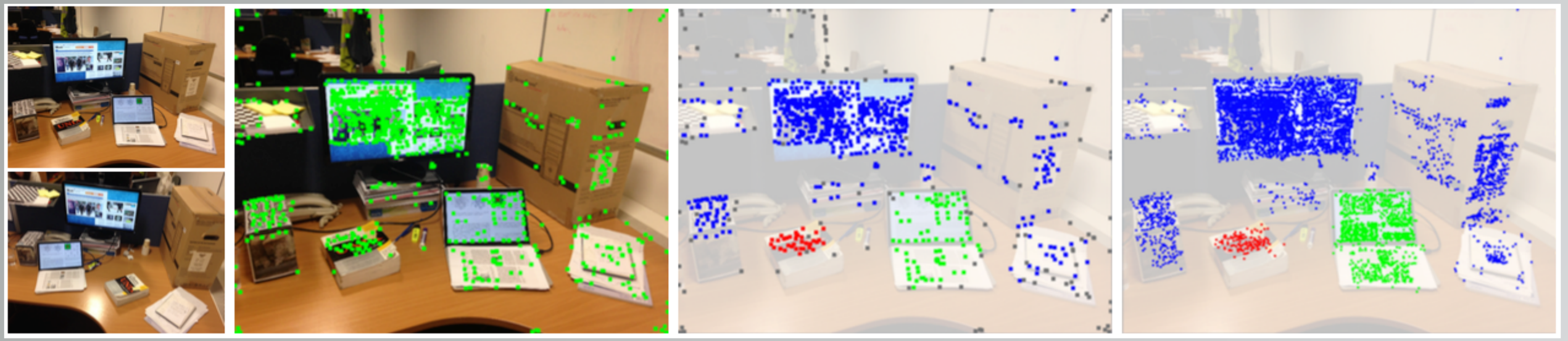

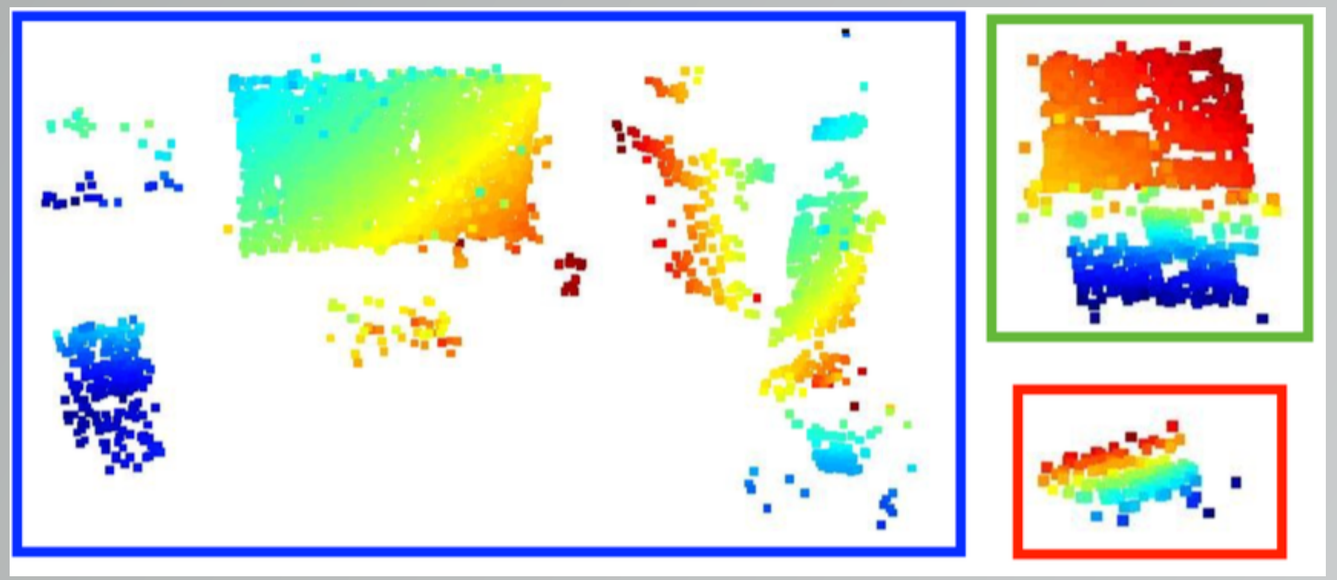

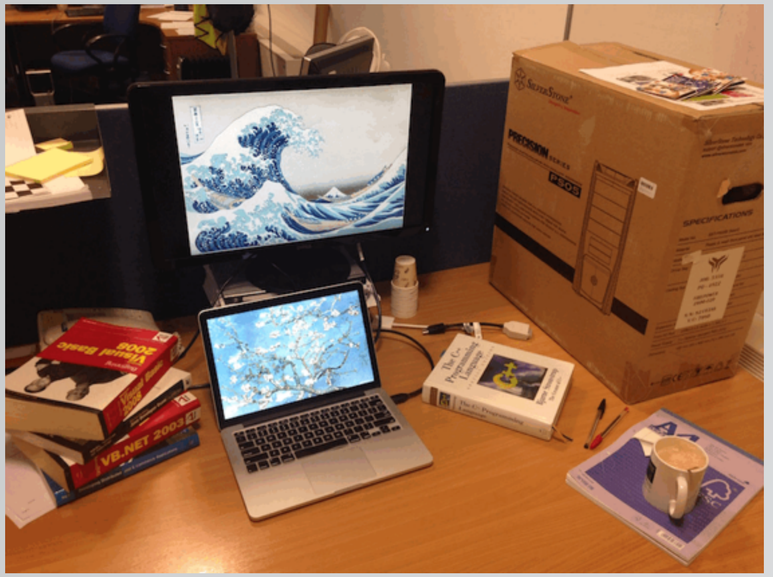

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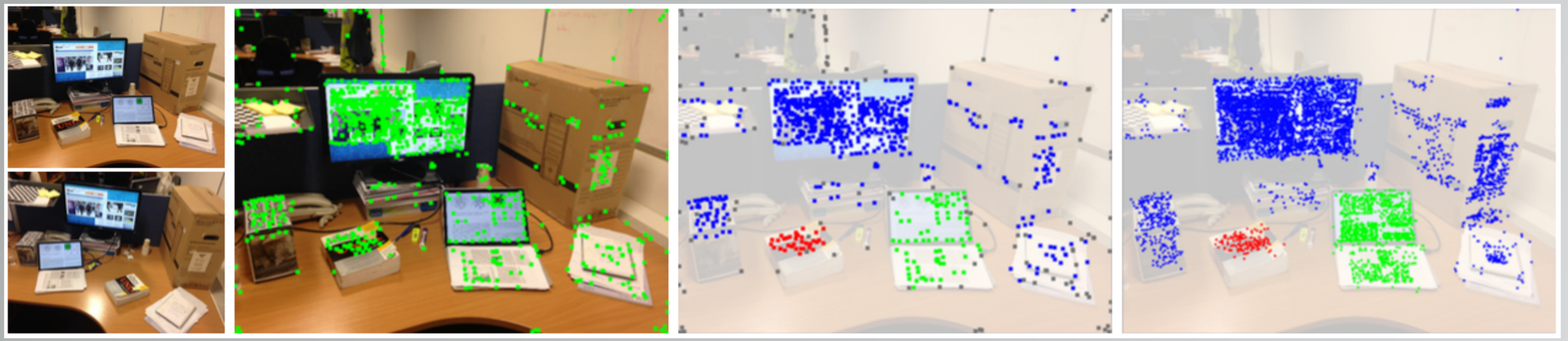

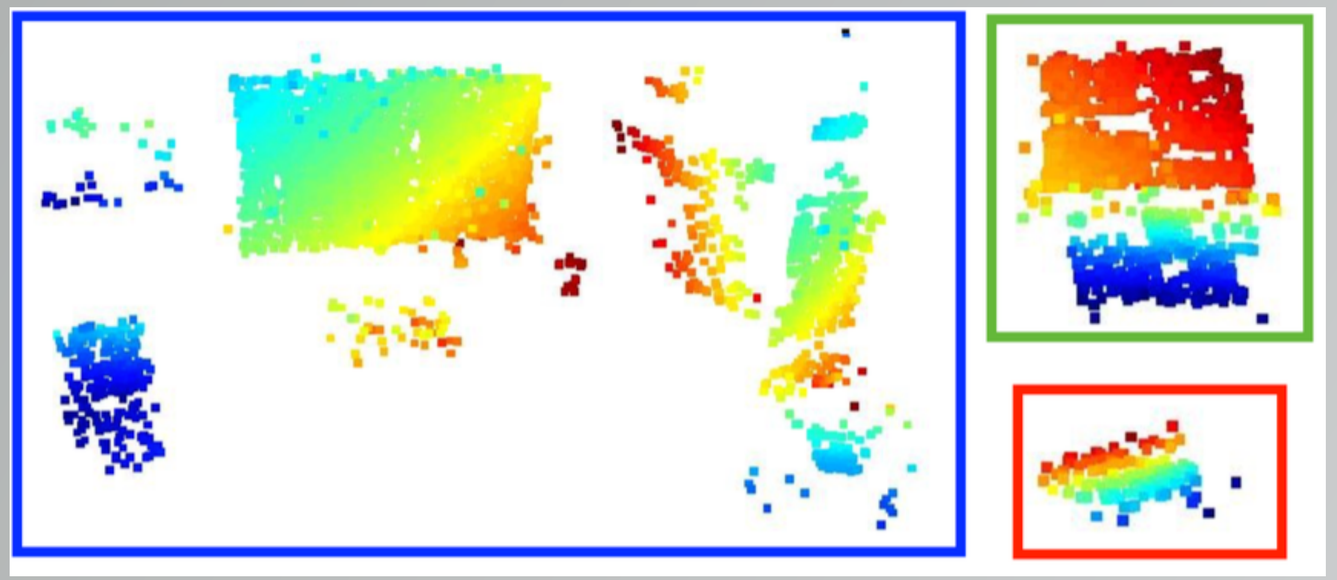

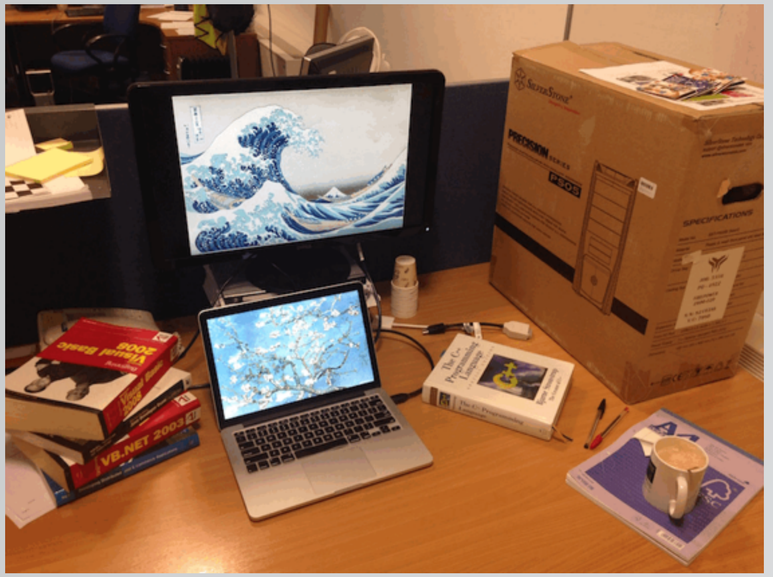

Dense Reconstruction

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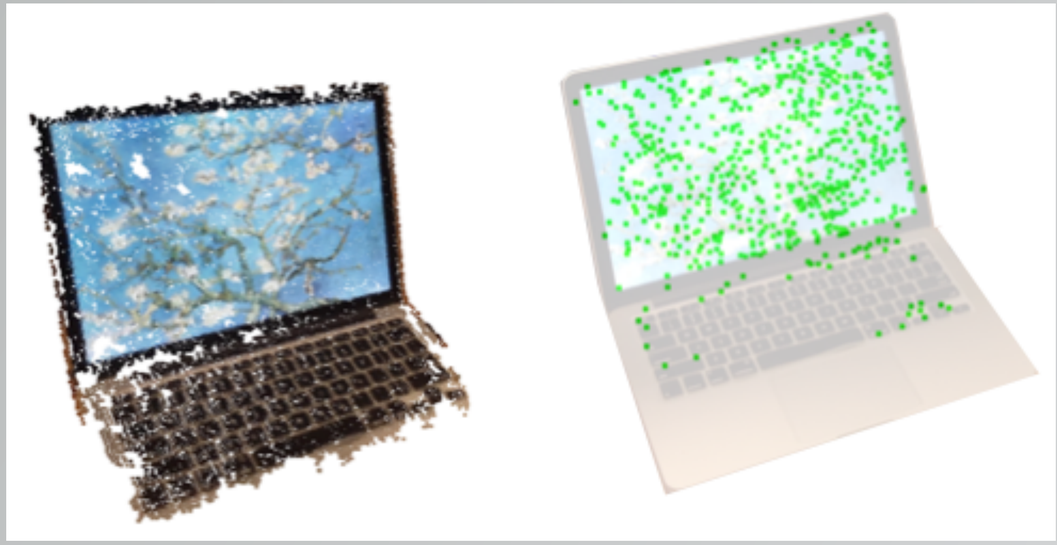
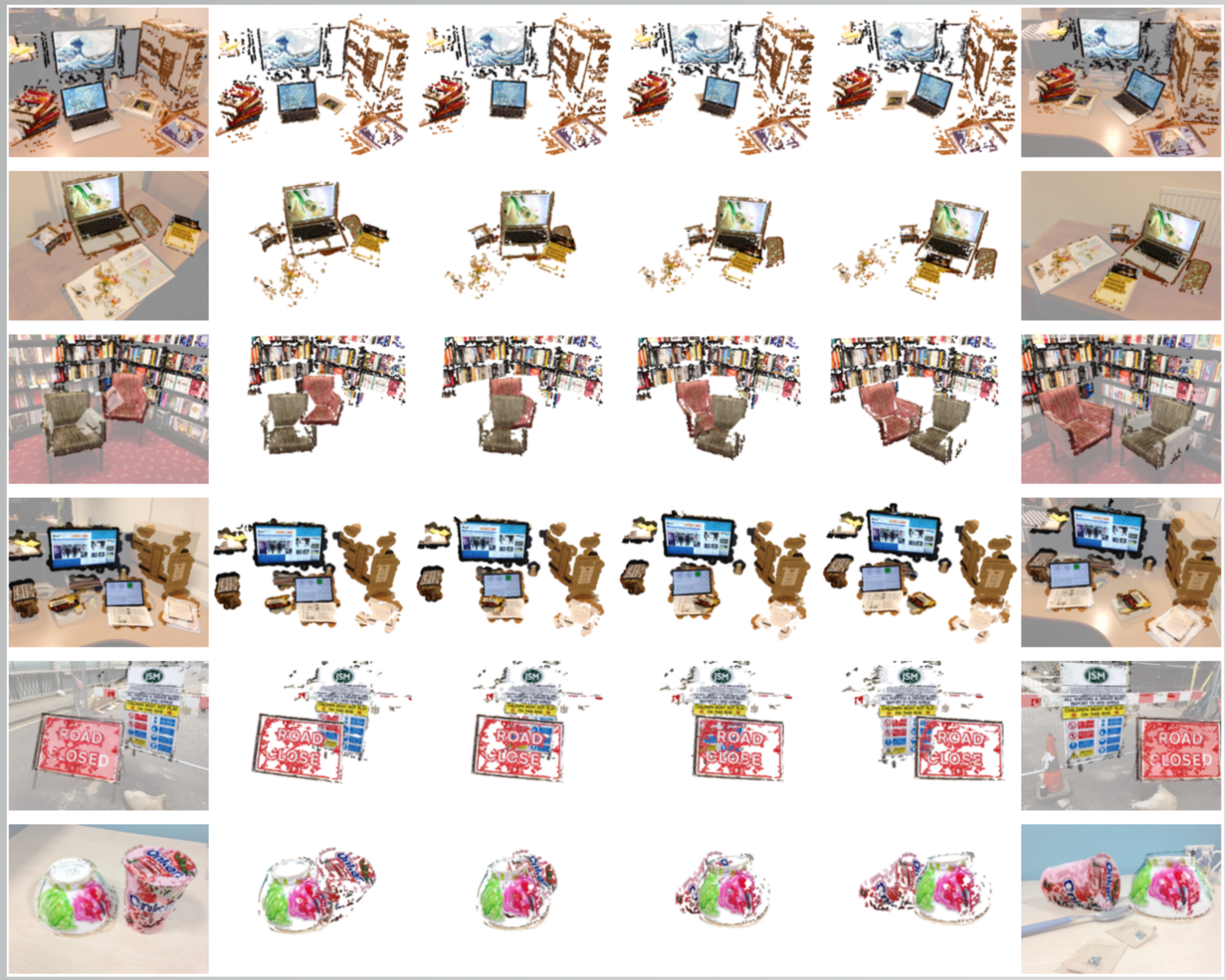


Application:

Motion Interpolation



Application:

Motion Interpolation

demo video available
on project page

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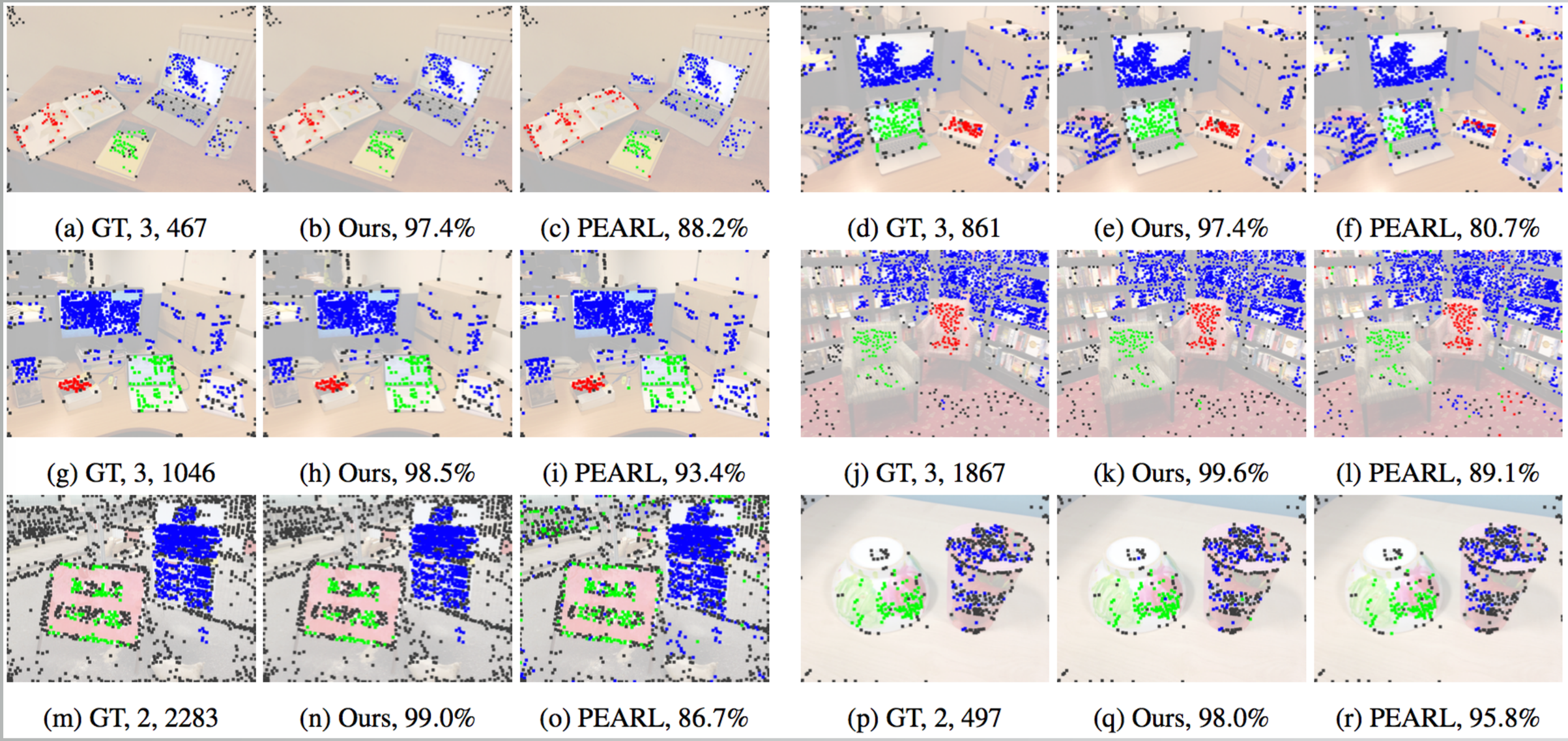
Comparison with PEARL



(a) GT, 3, 467 (b) Ours, 97.4% (c) PEARL, 88.2%

(d) GT, 3, 861 (e) Ours, 97.4% (f) PEARL, 80.7%

(g) GT, 3, 1046 (h) Ours, 98.5% (i) PEARL, 93.4%

(j) GT, 3, 1867 (k) Ours, 99.6% (l) PEARL, 89.1%

(m) GT, 2, 2283 (n) Ours, 99.0% (o) PEARL, 86.7%

(p) GT, 2, 497 (q) Ours, 98.0% (r) PEARL, 95.8%

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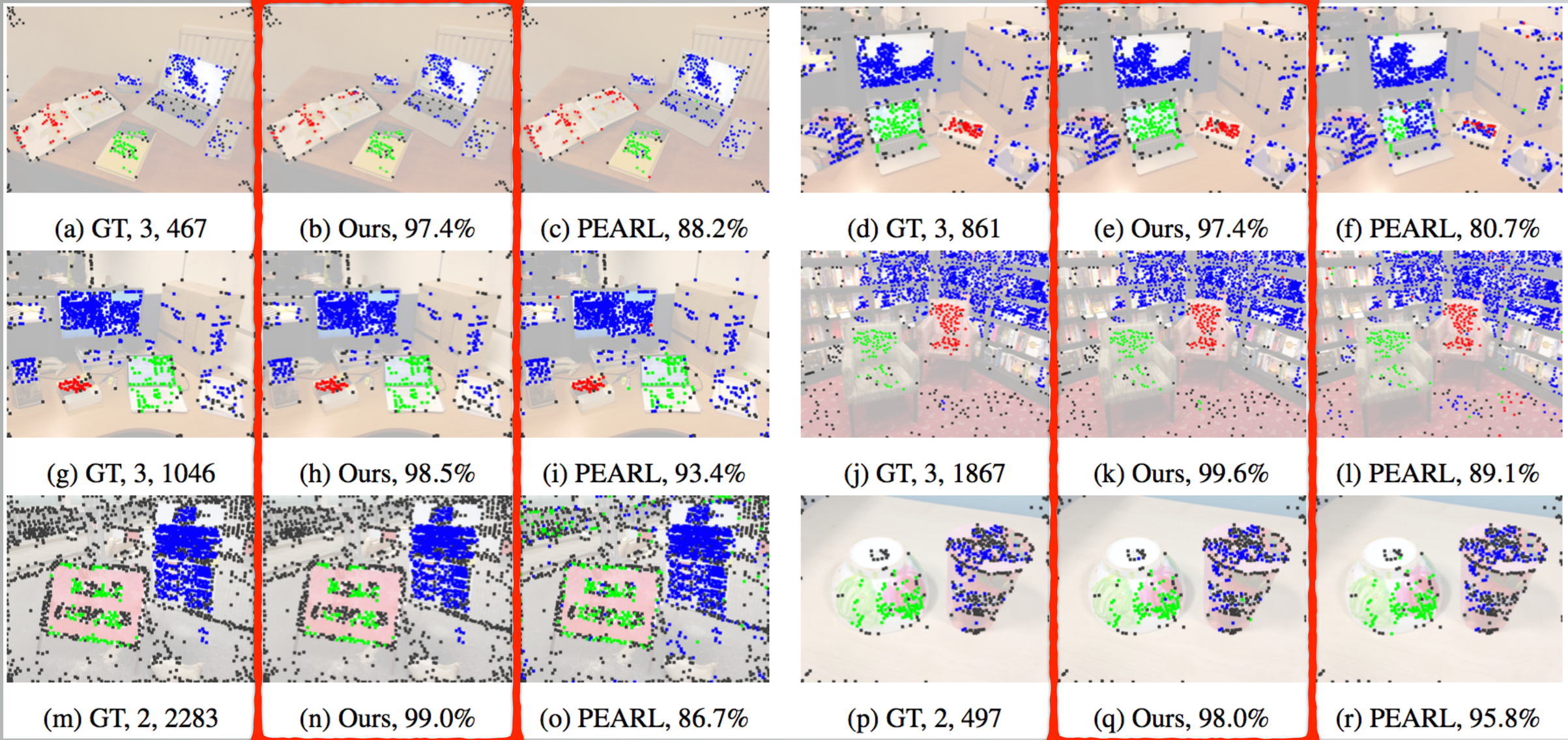

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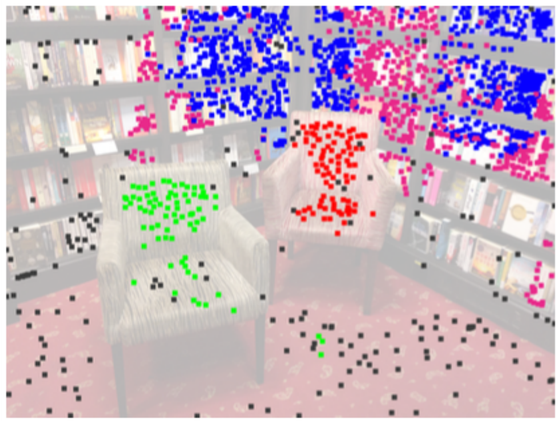
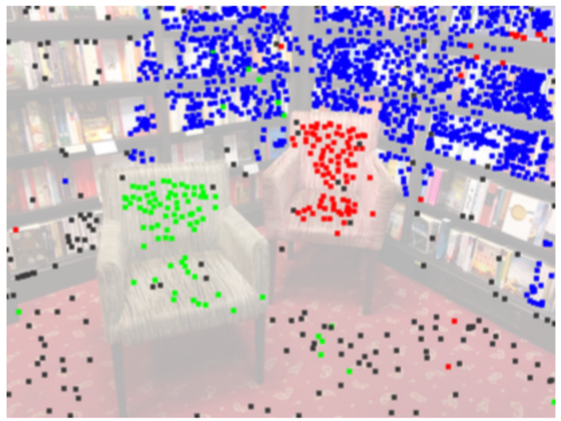
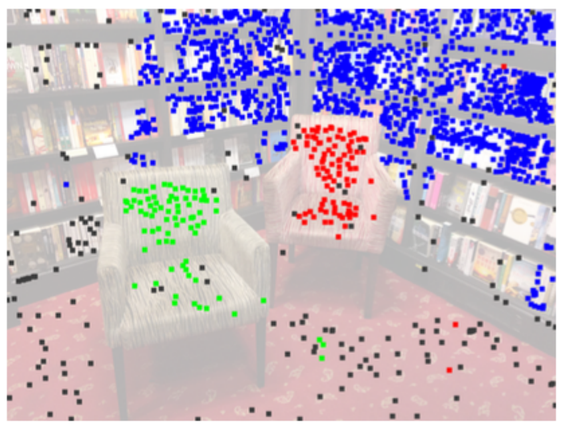
Effect of Terms



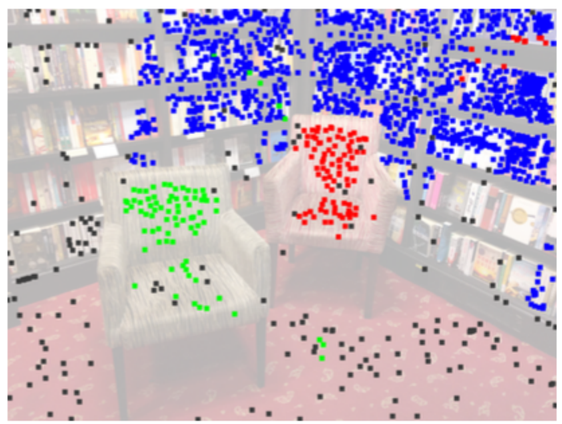
(a) no complexity term, 4 groups are generated.



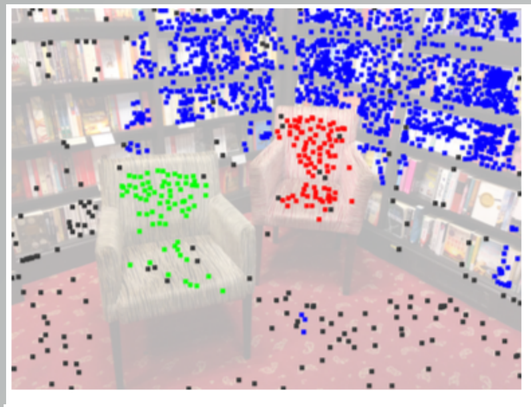
(b) uniform outlier penalty without consistency, correctness 97.4%



(c) uniform outlier penalty, correctness ratio 98.8%



(d) no consistency term, correctness ratio 98.3%



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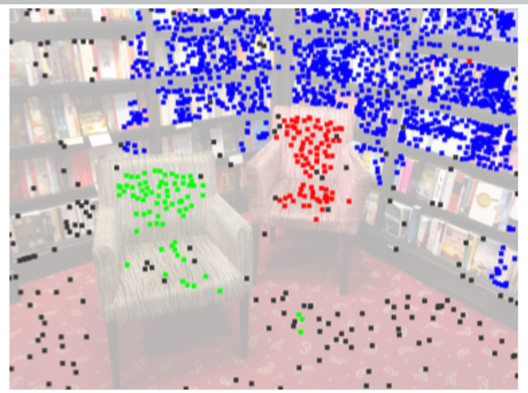
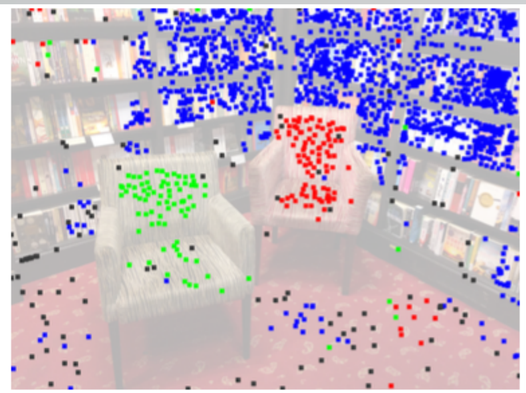
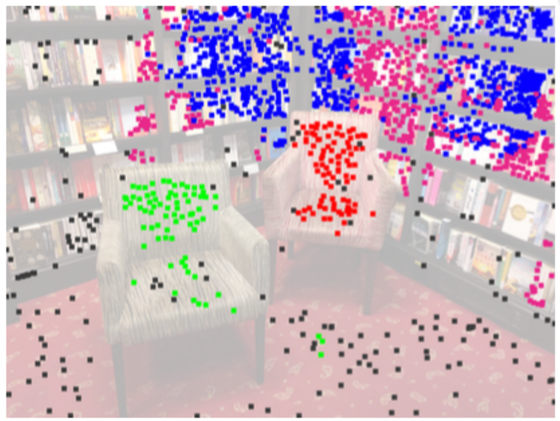


Ours , 99.6%

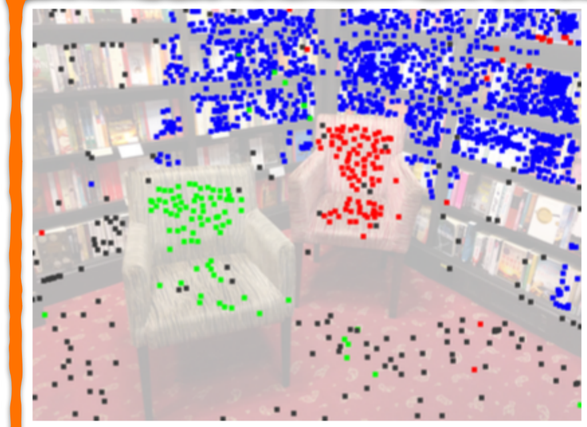


PEARL , 89.1%

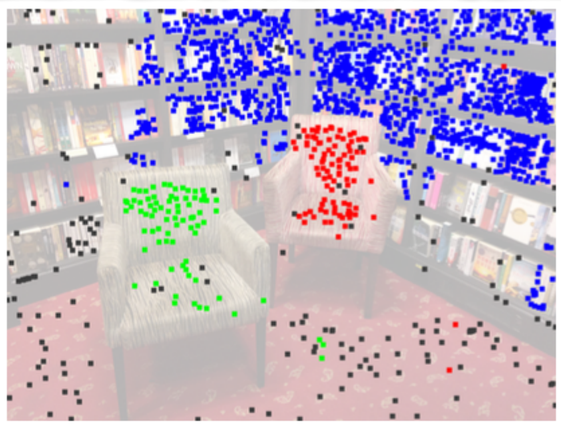
Effect of Terms



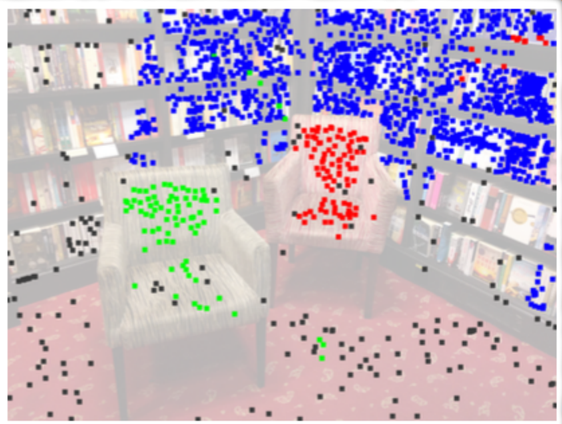
(a) no complexity term, 4 groups are generated.



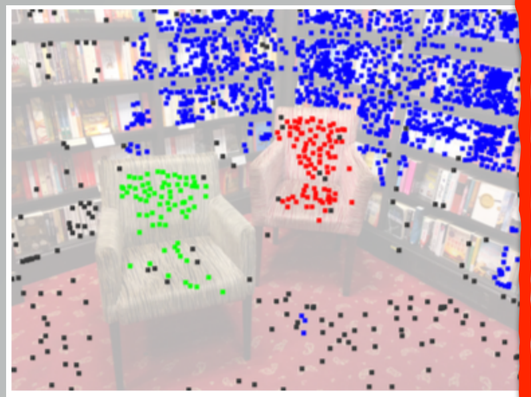
(b) uniform outlier penalty without consistency, correctness 97.4%



(c) uniform outlier penalty, correctness ratio 98.8%



(d) no consistency term, correctness ratio 98.3%



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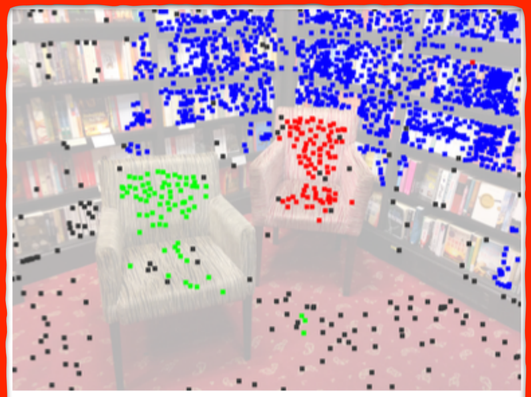
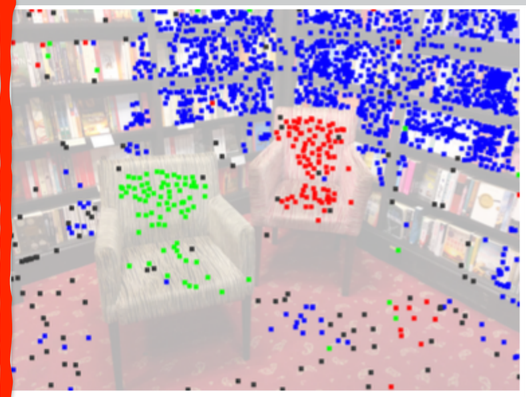


Ours , 99.6%



PEARL , 89.1%

Limitations

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- lack of texture

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- small change of perspective

Conclusion

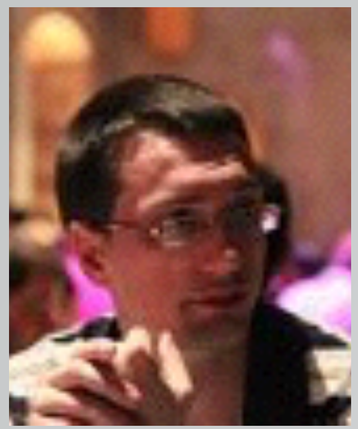
- **Dynamic SfM**
  - simultaneously recover both structure and motion of each part from a pair of input images
  - pre-boosting and post-boosting of correspondence

Conclusion

- **Dynamic SfM**
  - simultaneously recover both structure and motion of each part from a pair of input images
  - pre-boosting and post-boosting of correspondence
- **Future work**
  - prior knowledge of the structure
  - towards real time performance
  - multi-view input

Acknowledgement

- Invaluable comments, support and discussions from
  Aron Monszpart and **Duygu Ceylan** and **Christopher Russell**.



- This work was supported by ERC Starting Grant SmartGeometry (StG-2013335373) and Microsoft PhD scholarship

Microsoft® Research

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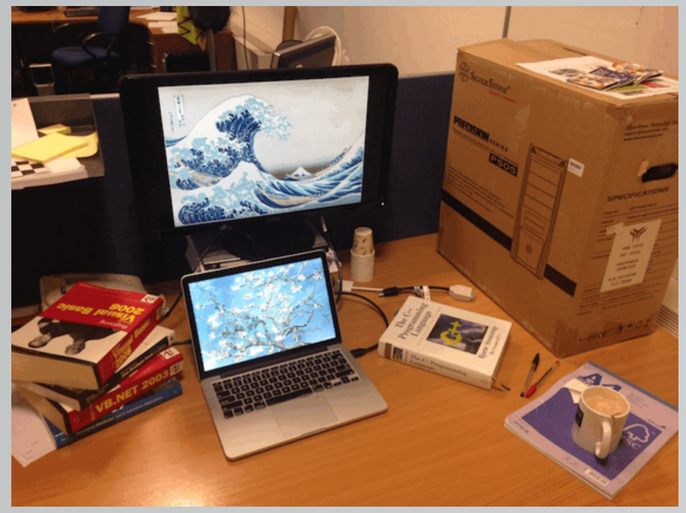
Thank you for your attention

- webpage (code+data)

http://geometry.cs.ucl.ac.uk/projects/2015/dynamicSfM/



Thank you for your attention

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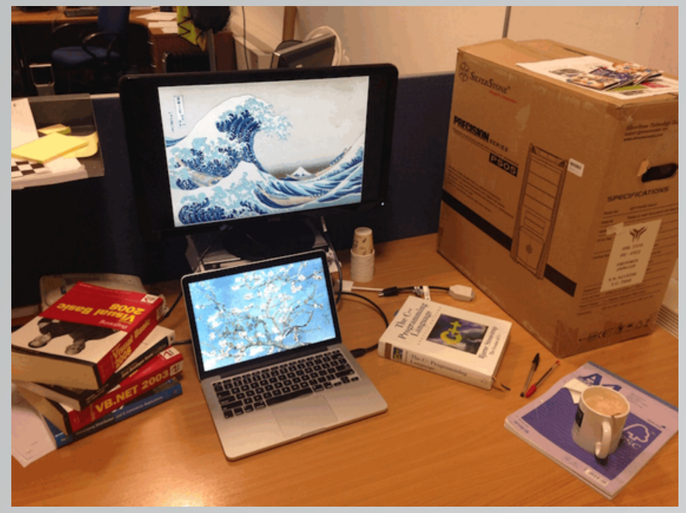
http://geometry.cs.ucl.ac.uk/projects/2015/dynamicSfM/