

BundleFusion: Real-time Globally Consistent 3D Reconstruction using On-the-fly Surface Re-integration

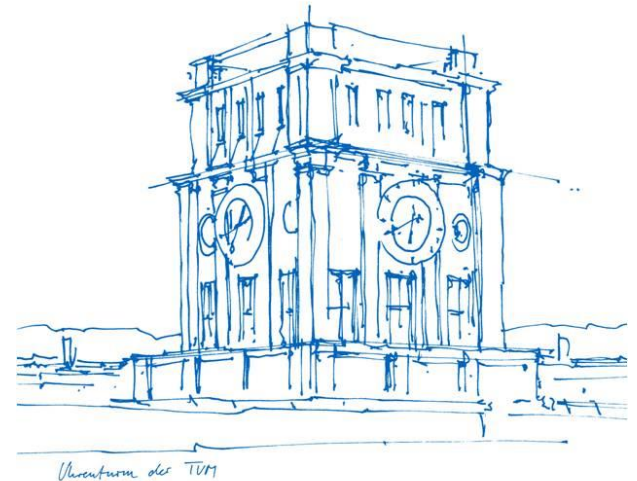
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Online 3D Reconstruction

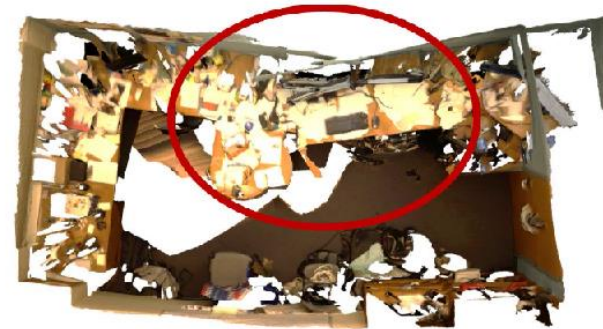
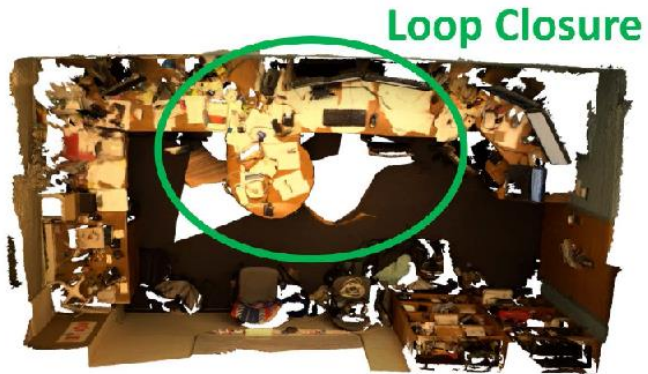


KinectFusion: first real-time volumetric fusion

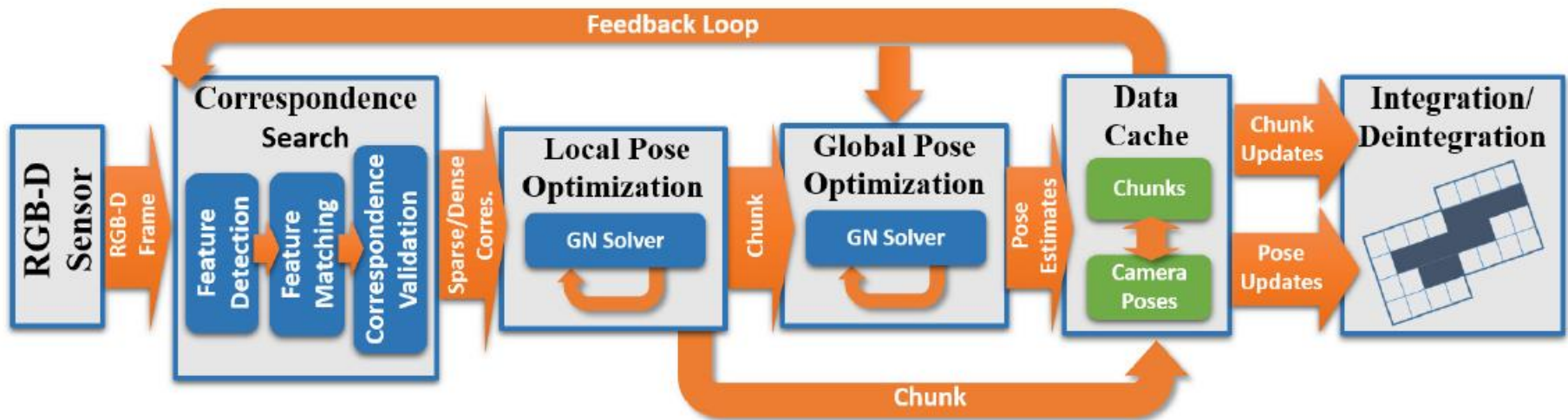
[*Newcombe et.al , Izadi et al 11*]

Online 3D Reconstruction: Challenges

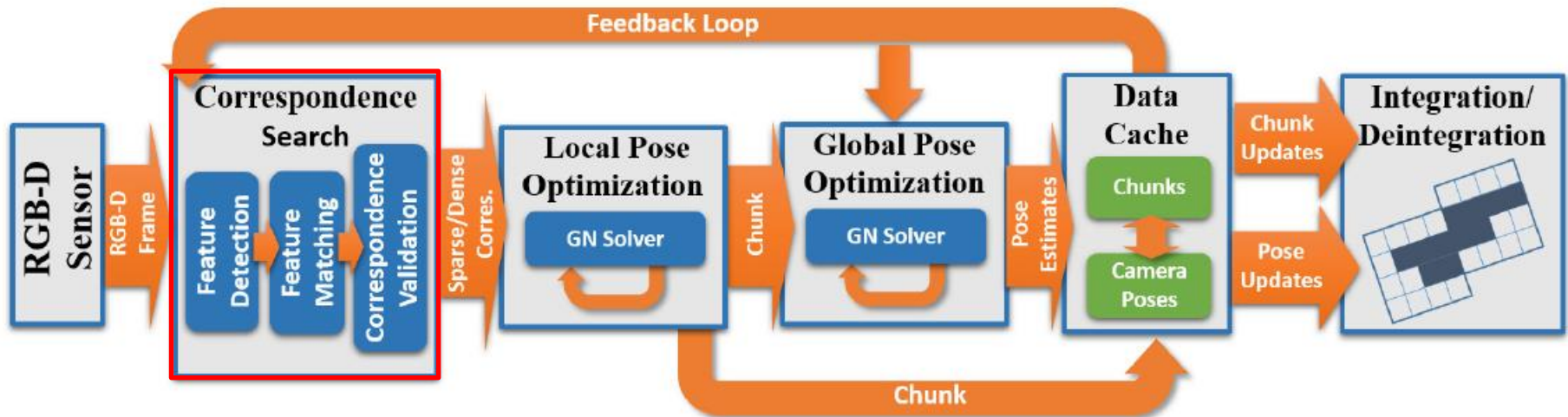
Tracking: global consistency, loop closure, re-localization



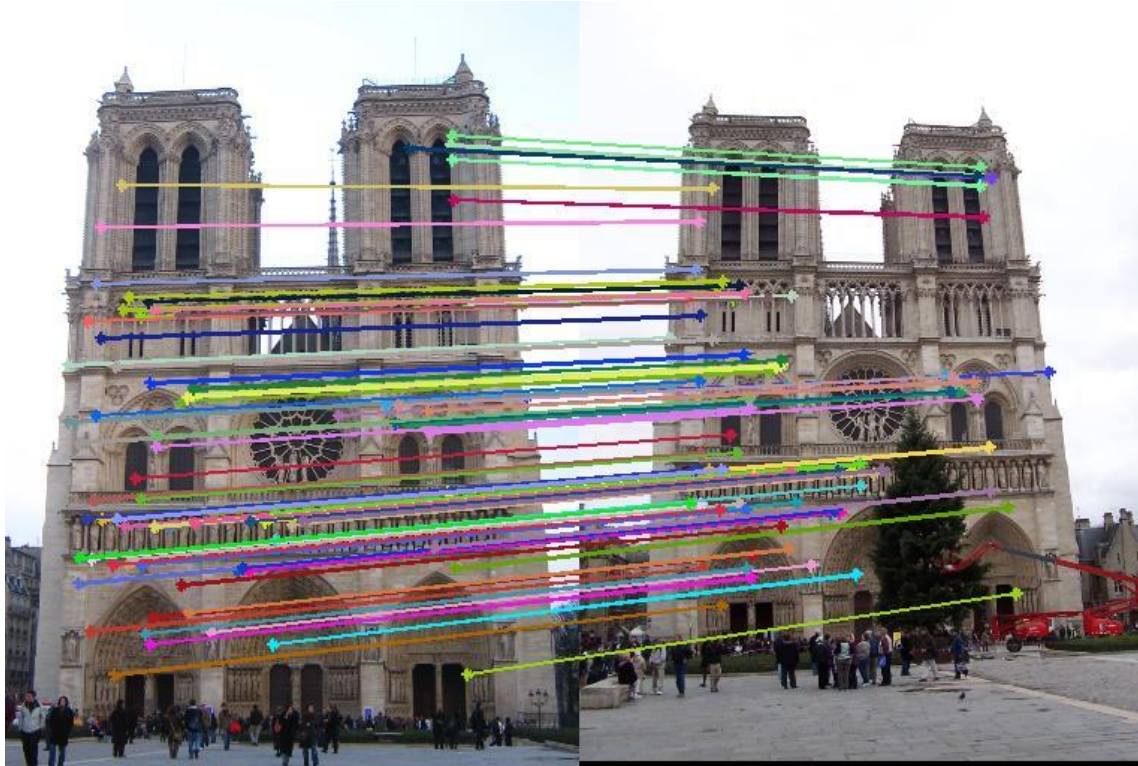
BundleFusion: Overview



BundleFusion: Overview



Correspondence Filtering



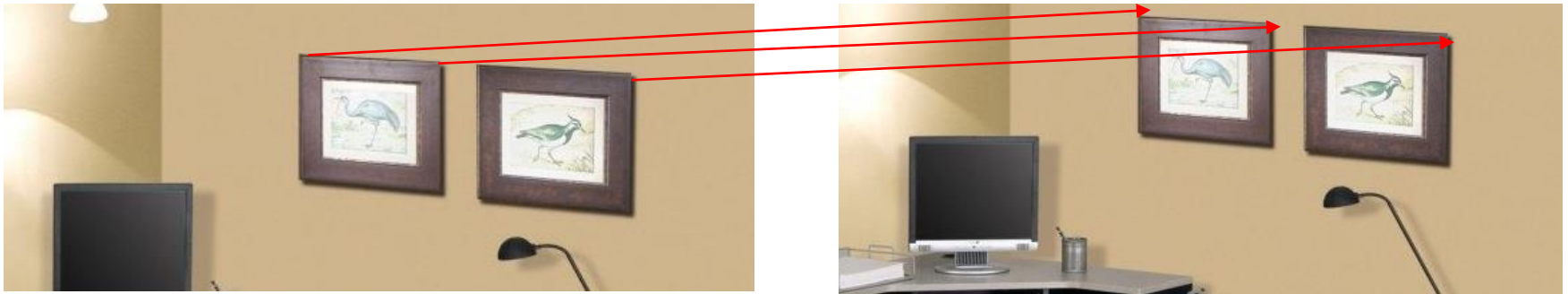
Example from Georgia Tech College of Computing

1. Key point correspondence filter: find consistent transform

Correspondence Filtering

2. Surface area filter: remove badly conditioned correspondence sets

Unstable transform



Images modeled from Foter.com

Correspondence Filtering

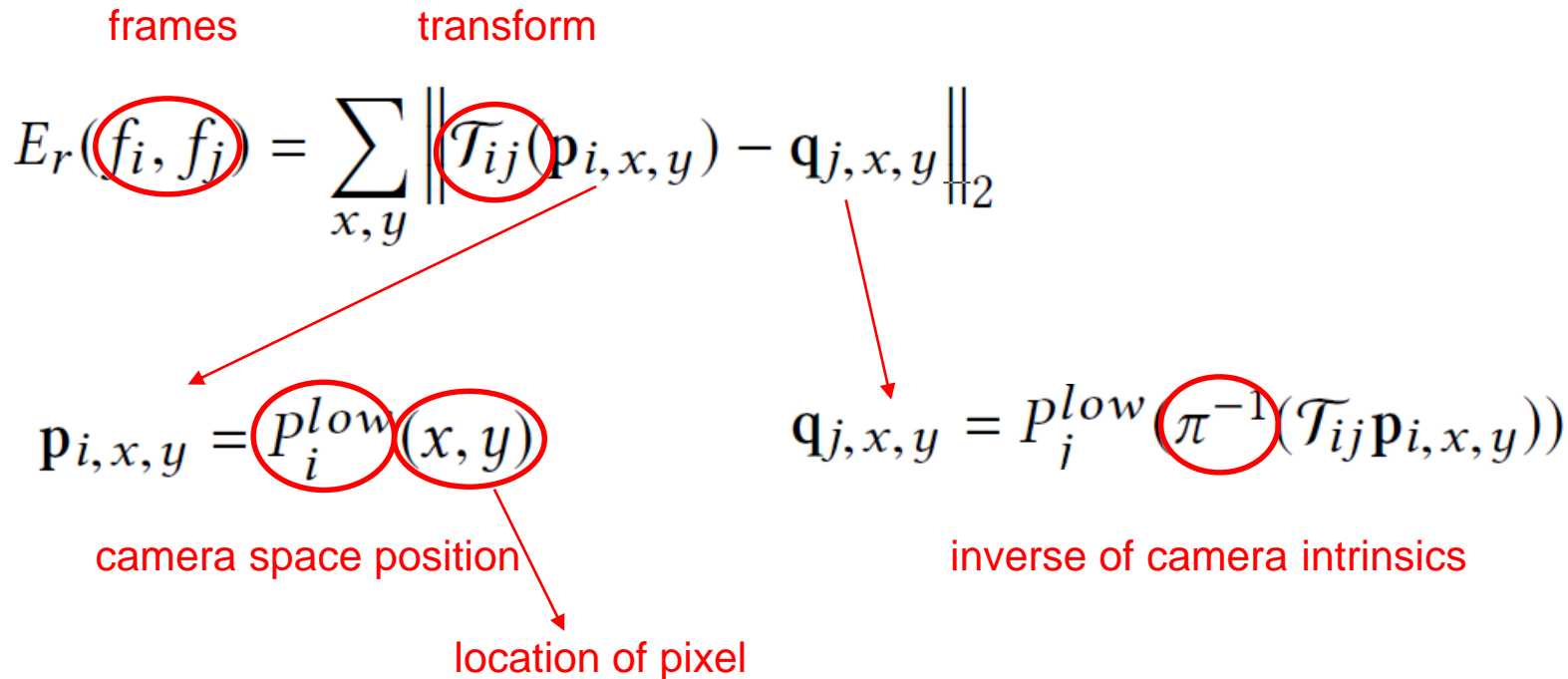
3. Dense projection: check high re-projection error

frames transform

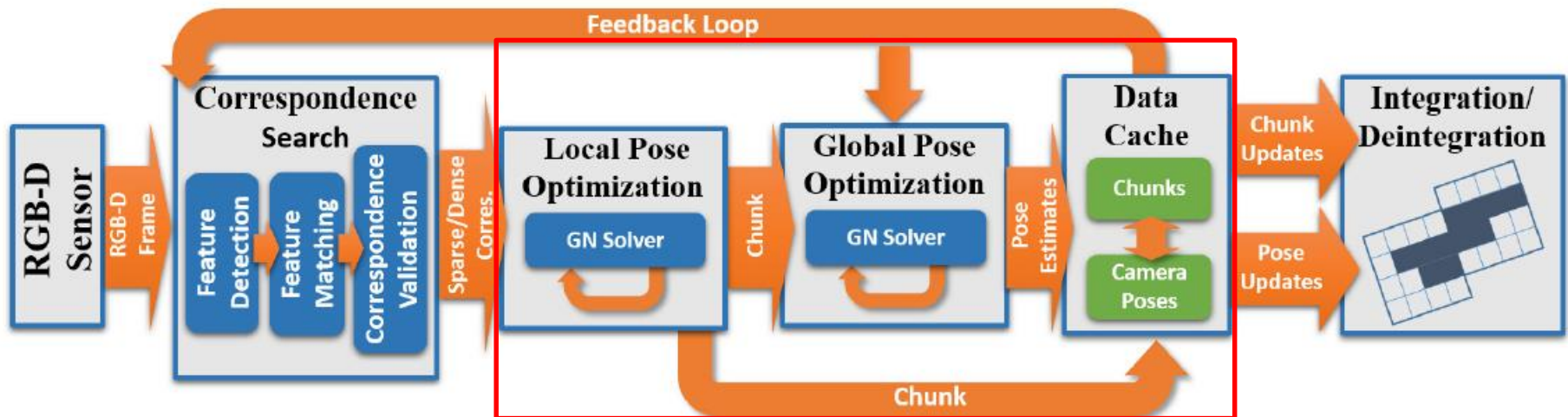
$$E_r(f_i, f_j) = \sum_{x,y} \left\| \mathcal{T}_{ij}(\mathbf{p}_{i,x,y}) - \mathbf{q}_{j,x,y} \right\|_2$$

$\mathbf{p}_{i,x,y} = P_i^{low}(x,y)$ camera space position location of pixel

$\mathbf{q}_{j,x,y} = P_j^{low}(\pi^{-1}(\mathcal{T}_{ij}\mathbf{p}_{i,x,y}))$ inverse of camera intrinsics



BundleFusion: Overview



Sparse-to-Dense Optimization

- Initialize with sparse features, continue with dense features
- Coarse to fine alignment

$$E_{\text{align}}(\mathcal{X}) = w_{\text{sparse}}E_{\text{sparse}}(\mathcal{X}) + w_{\text{dense}}E_{\text{dense}}(\mathcal{X}).$$

where

$$\mathcal{X} = (\mathbf{R}_0, \mathbf{t}_0, \dots, \mathbf{R}_{|S|}, \mathbf{t}_{|S|})^T = (x_0, \dots, x_N)^T$$

$$E_{\text{sparse}}(\mathcal{X}) = \sum_{i=1}^{|S|} \sum_{j=1}^{|S|} \sum_{(k,l) \in C(i,j)} \|\mathcal{T}_i \mathbf{p}_{i,k} - \mathcal{T}_j \mathbf{p}_{j,l}\|_2^2$$

pairwise correspondences

k-th feature point from i-th frame

Sparse-to-Dense Optimization

- fine scale alignment

$$E_{\text{dense}}(\mathcal{T}) = w_{\text{photo}} E_{\text{photo}}(\mathcal{T}) + w_{\text{geo}} E_{\text{geo}}(\mathcal{T})$$

$$E_{\text{photo}}(\mathcal{X}) = \sum_{(i,j) \in \mathbb{E}} \sum_{k=0}^{|\mathcal{I}_i|} \left\| \mathcal{I}_i(\pi(\mathbf{d}_{i,k})) - \mathcal{I}_j(\pi(\mathcal{T}_j^{-1} \mathcal{T}_i \mathbf{d}_{i,k})) \right\|_2^2$$

gradient of the luminance of frame color

3D projection of the k-th pixel of the i-th frame

perspective projection

$$E_{\text{geo}}(\mathcal{X}) =$$

$$\sum_{(i,j) \in \mathbb{E}} \sum_{k=0}^{|\mathcal{D}_i|} \left[\mathbf{n}_{i,k}^T (\mathbf{d}_{i,k} - \mathcal{T}_i^{-1} \mathcal{T}_j \pi^{-1} (\mathcal{D}_j (\pi(\mathcal{T}_j^{-1} \mathcal{T}_i \mathbf{d}_{i,k})))) \right]^2$$

normal of the k-th pixel of the i-th frame

depth

Sparse-to-Dense Optimization: Example

Full



Sparse



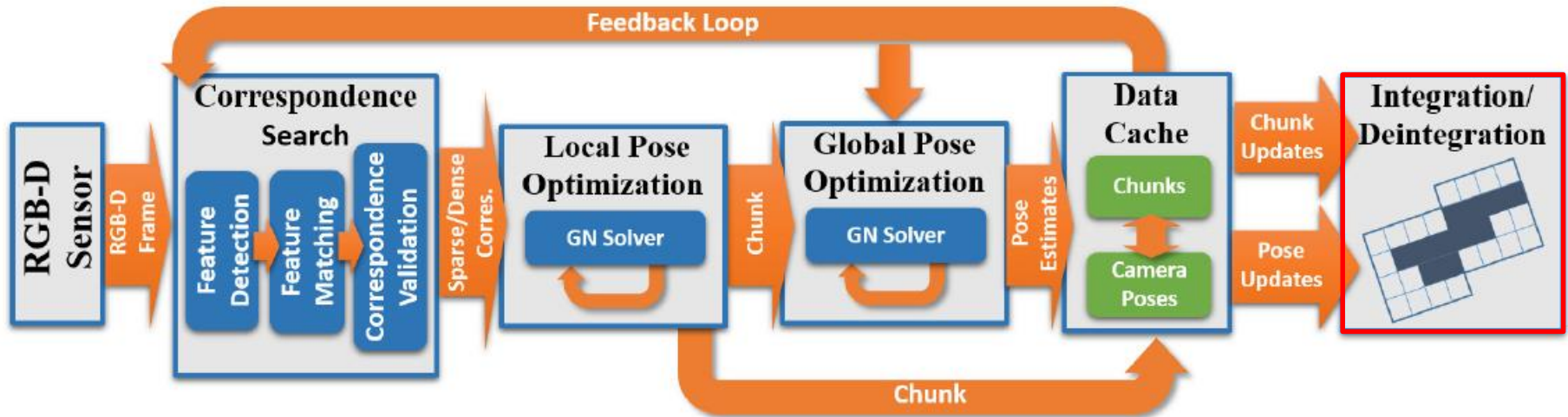
Local-to-Global Strategy

1. Local Intra-Chunk Pose Optimization

2. Per-Chunk Keyframes

3. Global Inter-Chunk Pose Optimization

BundleFusion: Overview



Dynamic Scene Update: On-the-fly

- Surface Integration

signed distance of the voxel

projective distance

voxel {
 distance;
 color;
 weight;
 }

$$D'(\mathbf{v}) = \frac{D(\mathbf{v})W(\mathbf{v}) + w_i(\mathbf{v})d_i(\mathbf{v})}{W(\mathbf{v}) + w_i(\mathbf{v})}$$

$$W'(\mathbf{v}) = W(\mathbf{v}) + w_i(\mathbf{v})$$

voxel weight integration weight

Dynamic Scene Update: On-the-fly

- Surface De-Integration: remove d_i from weighted average

```
voxel {  
  distance;  
  color;  
  weight;  
}
```

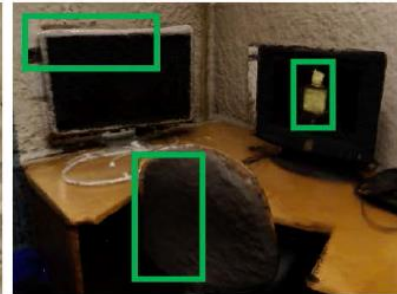
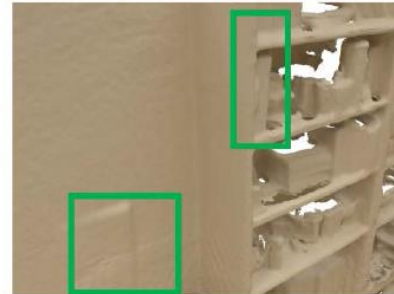
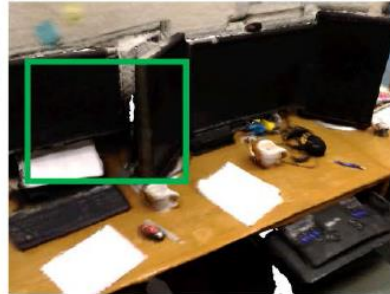
$$D'(\mathbf{v}) = \frac{D(\mathbf{v})W(\mathbf{v}) - w_i(\mathbf{v})d_i(\mathbf{v})}{W(\mathbf{v}) - w_i(\mathbf{v})}$$
$$W'(\mathbf{v}) = W(\mathbf{v}) - w_i(\mathbf{v})$$

Results



Results

Ours
(online)



ElasticFusion
(online)



Performance

- Dual GPU Performance – global dense optimization <500ms

$$\mathcal{X}^* = \operatorname{argmin}_{\mathcal{X}} E_{align}(\mathcal{X})$$

- Tailored Gauss Newton solver

Conclusions

- Real-time reconstruction with commodity RGB-D sensors
- Global pose optimization
- Online loop closures
- Real-time re-localization
- On-the-fly scene updates