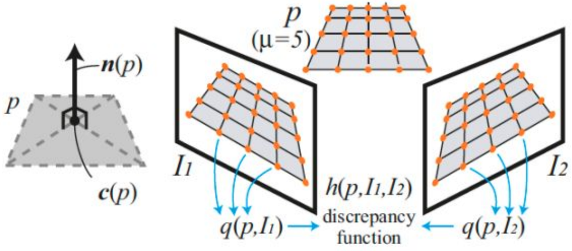
Accurate, Dense, and Robust Multi-View Stereopsis

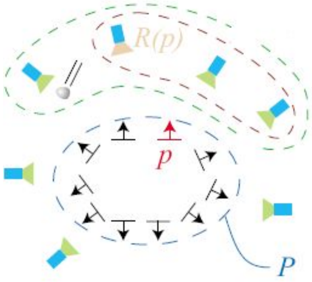
Authors: Yasutaka Furukawa, Jean Ponce
Presenter: Nail Ibrahimli

In one slide :)

1. Detect keypoints
2. Triangulate a sparse set of initial matches
3. Iteratively expand matches to nearby locations
4. Use visibility constraints to filter out false matches
5. Perform surface reconstruction

Patch Model

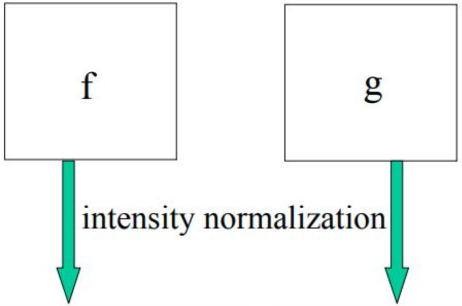




c(p): center of the patch
n(p): normal of the patch
R(p): reference image with p

$$\mathbf{c}(p) \leftarrow \{\text{Triangulation from } f \text{ and } f'\},$$
$$\mathbf{n}(p) \leftarrow \overrightarrow{\mathbf{c}(p)O(I_i)} / |\overrightarrow{\mathbf{c}(p)O(I_i)}|,$$
$$R(p) \leftarrow I_i.$$

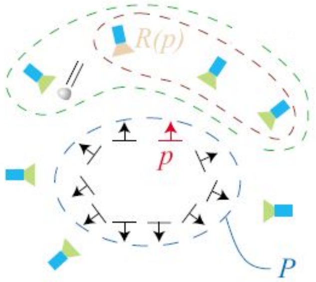
normalized cross correlation: quick glance



$$\hat{f} = \frac{f - \bar{f}}{\sqrt{\sum (f - \bar{f})^2}} \qquad \hat{g} = \frac{g - \bar{g}}{\sqrt{\sum (g - \bar{g})^2}}$$

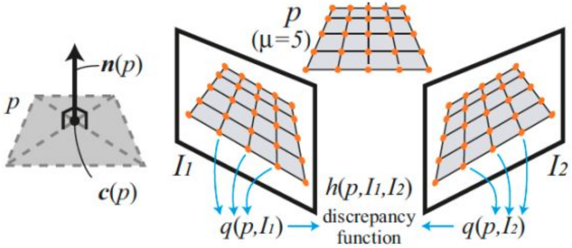
$$\text{NCC(f,g)} = C_{fg}(\hat{f}, \hat{g}) = \sum_{[i,j]\in R} \hat{f}(i,j)\hat{g}(i,j)$$

Photometric Discrepancy Function



$$h(p, I, R(p)) = 1 - NCC(p, I, R(p))$$

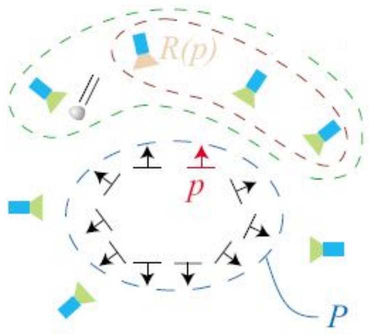
$$g(p) = \frac{1}{|V(p) \setminus R(p)|} \sum_{I \in V(p) \setminus R(p)} h(p, I, R(p)),$$



V(p): initial set of images where patch p is potentially visible

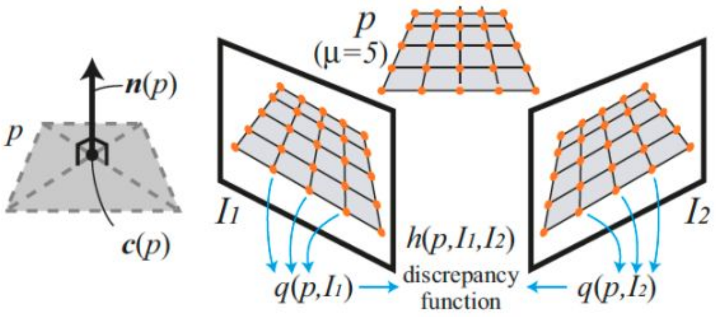
Photometric Discrepancy Function

$$
\begin{aligned}
V^*(p) &= \{I \mid I \in V(p), h(p, I, R(p)) \le \alpha\}, \\
g^*(p) &= \frac{1}{|V^*(p) \setminus R(p)|} \sum_{I \in V^*(p) \setminus R(p)} h(p, I, R(p)).
\end{aligned}
$$



V*(p): set of images where patch is truly visible

Patch optimization

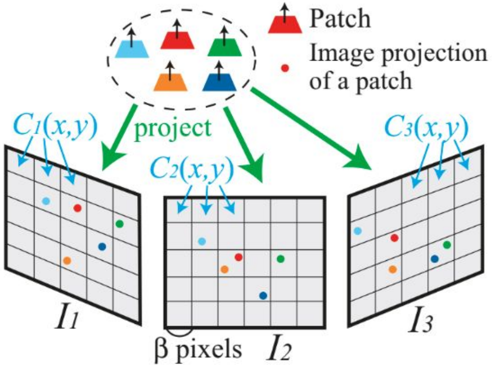


$$h(p, I, R(p)) = 1 - NCC(p, I, R(p))$$

$$g^*(p) = \frac{1}{|V^*(p) \setminus R(p)|} \sum_{I \in V^*(p) \setminus R(p)} h(p, I, R(p))$$

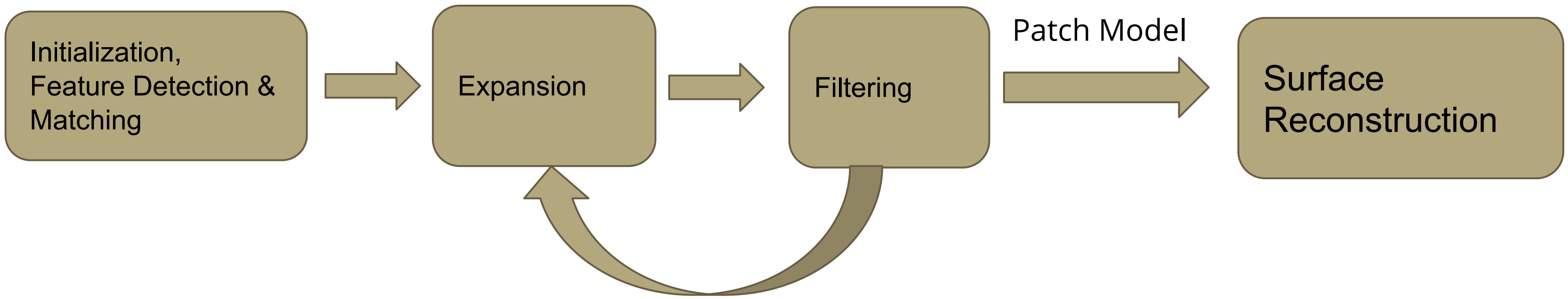
Optimize over c(p) and n(p) that minimizes g*(p)

Image model

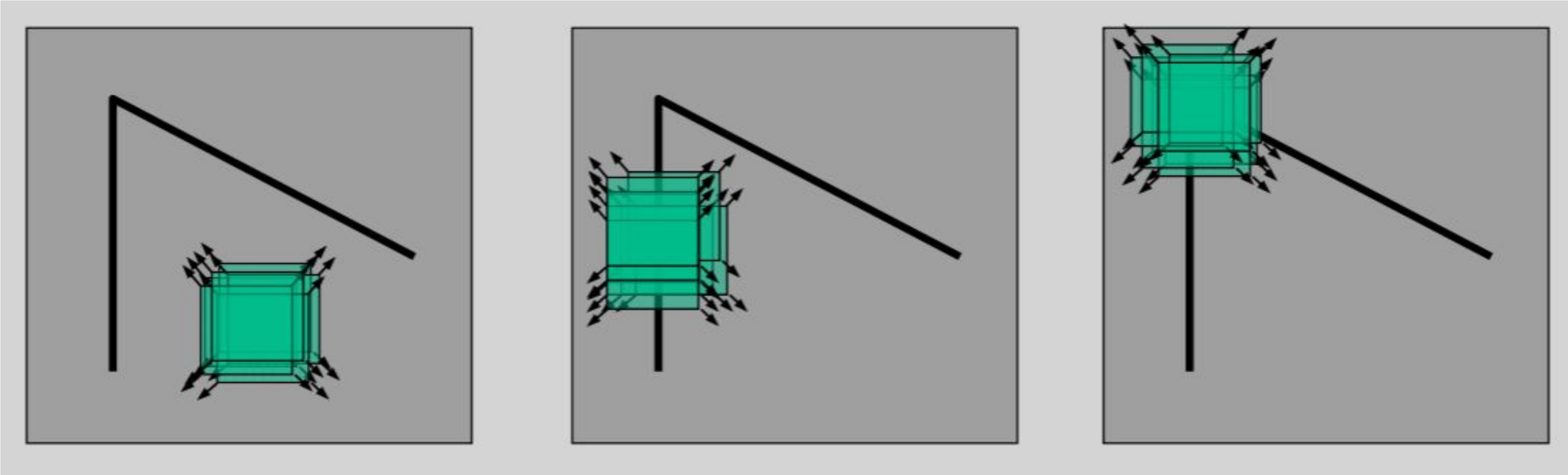


V(p): set of images where patch may be visible
V*(p): set of images where patch truly visible
C_i(x,y): regular grid cell $\beta \times \beta$ pixels
Q_i(x,y): the set of “may be” visible patches that projects to C_i(x,y)
Q*_i(x,y): the set of “truly visible”patches that projects to C_i(x,y)

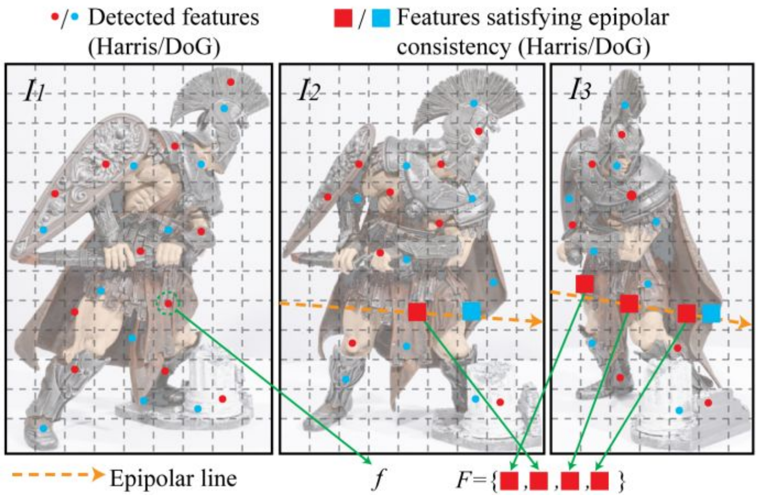
Flow diagram



Quick glance to corners: Aperture problem



Feature Detection

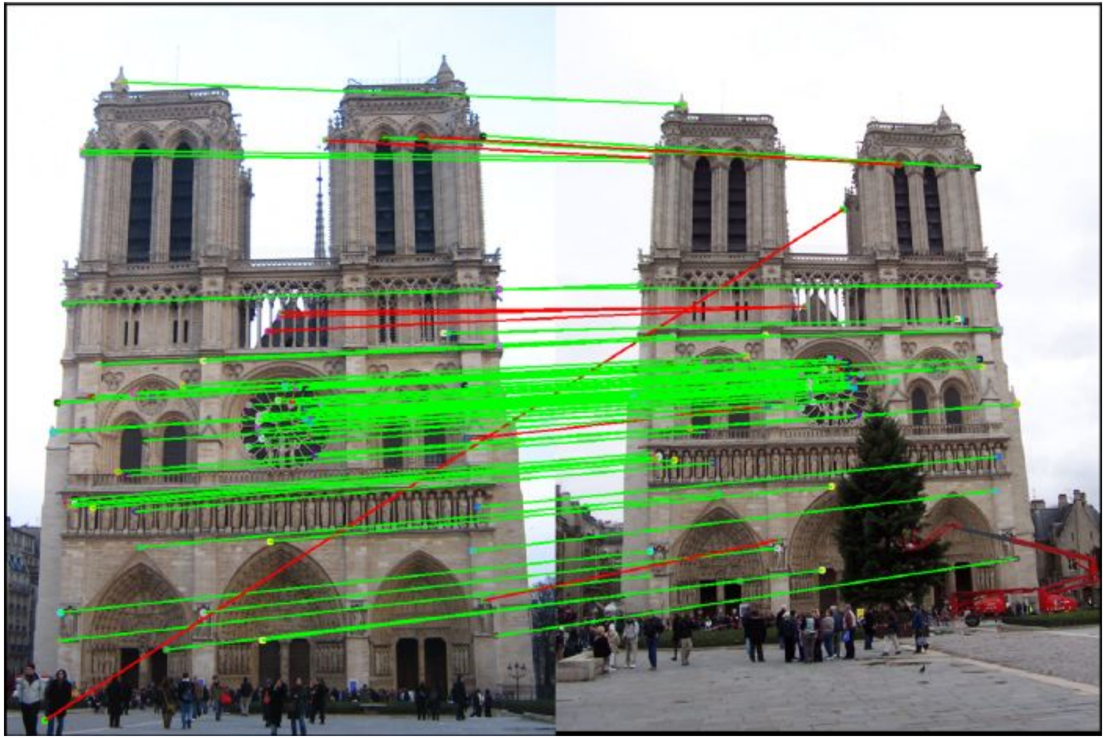


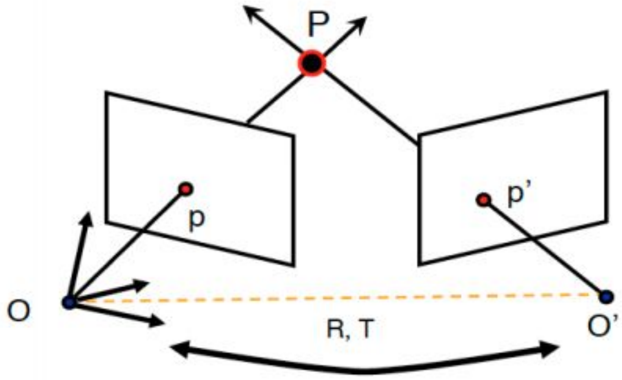
1. Divide grid to cells (32x32)

2. Use Harris Detector and DoG to find corners

3. Try to find 4 good corners in each cell (uniform coverage)

Quick glance: typical feature matching pipeline





$$p'^T K'^{-T} [T_\times] R K^{-1} p = 0$$

F

Detection → Description → Matching → Filtering

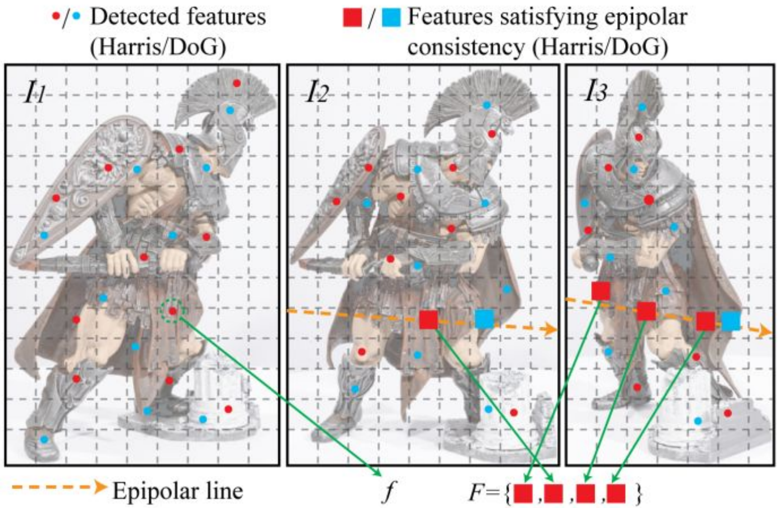
Feature Matching

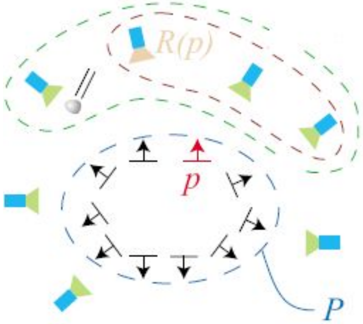
1. Epipolar line test for right matches
2. Initialization of patches

$$\mathbf{c}(p) \leftarrow \{\text{Triangulation from } f \text{ and } f'\},$$
$$\mathbf{n}(p) \leftarrow \overrightarrow{\mathbf{c}(p)O(I_i)}/|\overrightarrow{\mathbf{c}(p)O(I_i)}|,$$
$$R(p) \leftarrow I_i.$$

$$V(p) \leftarrow \left\{ I | \mathbf{n}(p) \cdot \overrightarrow{\mathbf{c}(p)O(I)}/|\overrightarrow{\mathbf{c}(p)O(I)}| > \cos(\iota) \right\}$$
$$V^*(p) = \{ I | I \in V(p), h(p,I,R(p)) \leq \alpha \}$$

3. Refine patch geometry



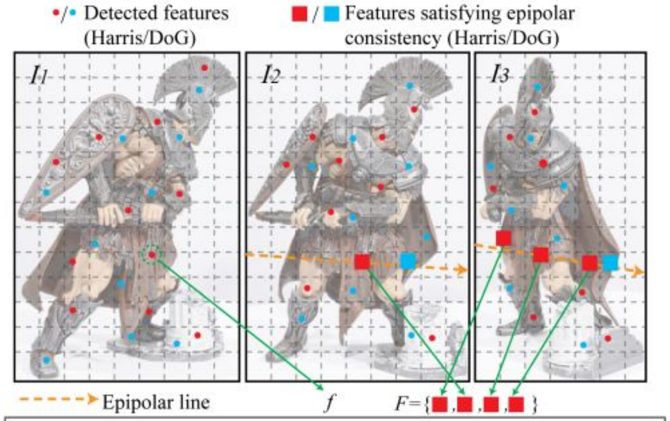


Feature Matching

4. Update the V(p) and V*(p) with
   refined patch geometry

5. Check if patch truly visible in at least γ images

6. Add valid patches to corresponding Q and Q*



Input: Features detected in each image.
Output: Initial sparse set of patches P.

$P \leftarrow \phi$;
For each image I with optical center $O(I)$
  For each feature f detected in I
    $F \leftarrow$ {Features satisfying the epipolar consistency};
    Sort F in an increasing order of distance from $O(I)$);
    For each feature $f' \in F$
      // Test a patch candidate p;
      Initialize $\mathbf{c}(p), \mathbf{n}(p)$ and $R(p)$; // Eqs. (4, 5, 6)
      Initialize $V(p)$ and $V^*(p)$; // Eqs. (2, 7)
      Refine $\mathbf{c}(p)$ and $\mathbf{n}(p)$; // (Sect.II-C)
      Update $V(p)$ and $V^*(p)$; // Eqs. (2, 7)
      If $|V^*(p)| < \gamma$
        Go back to the innermost *For* loop (failure);
      Add p to the corresponding $Q_j(x,y)$ and $Q_j^*(x,y)$;
      Remove features from the cells where p was stored;
      Add p to P;
      Exit innermost *For* loop;

Expansion

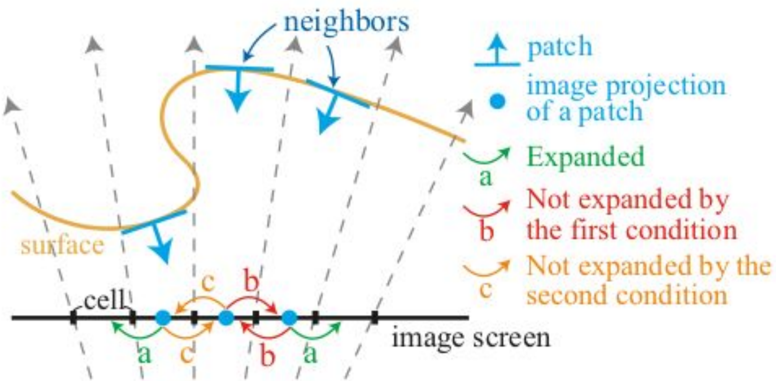
1. Identify neighboring cells for possible expansion

$$\mathbf{C}(p) = \{C_i(x', y') | p \in Q_i(x, y), |x - x'| + |y - y'| = 1\}$$

2. Test if there is already patch very close to that region

$$|(\mathbf{c}(p) - \mathbf{c}(p')) \cdot \mathbf{n}(p)| + |(\mathbf{c}(p) - \mathbf{c}(p')) \cdot \mathbf{n}(p')| < 2\rho_1$$

3. Test for depth discontinuity



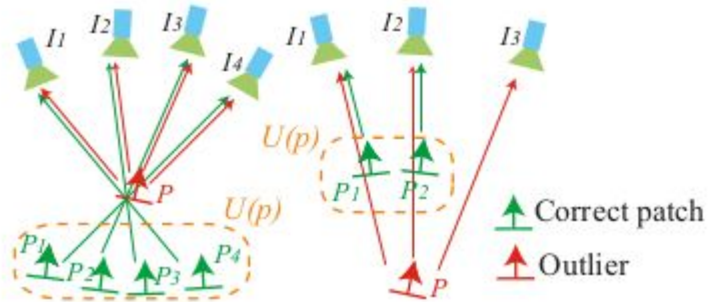
Expansion

4. Initialize candidate patch
5. Refine patch geometry
6. Update the V(p) and V*(p) with
   refined patch geometry (loosen thresholds)
7. Check if patch truly visible in at least γ images
8. Add valid patches to corresponding Q and Q*

Input: Patches P from the feature matching step.
Output: Expanded set of reconstructed patches.

While P is not empty
  Pick and remove a patch p from P;
  For each image cell $C_i(x,y)$ containing p
    Collect a set $\mathbf{C}$ of image cells for expansion;
    For each cell $C_i(x',y')$ in $\mathbf{C}$
      // Create a new patch candidate p'
      $\mathbf{n}(p') \leftarrow \mathbf{n}(p)$, $R(p') \leftarrow R(p)$, $V(p') \leftarrow V^*(p')$;
      Update $V^*(p')$; // Eq. (2)
      Refine $\mathbf{c}(p')$ and $\mathbf{n}(p')$; // (Sect.II-C)
      Add visible images (a depth-map test) to $V(p')$;
      Update $V^*(p')$; // Eq. (2)
      If $|V^*(p')| < \gamma$
        Go back to *For*-loop (failure);
      Add p' to P;
      Add p' to corresponding $Q_j(x,y)$ and $Q_j^*(x,y)$;

Filtering



First filter: Global visibility consistency

$$|V^*(p)|(1-g^*(p)) < \sum_{p_i \in U(p)} 1 - g^*(p_i)$$

Second filter: Depth map test

check if patch truly visible in at least γ images after depth map test

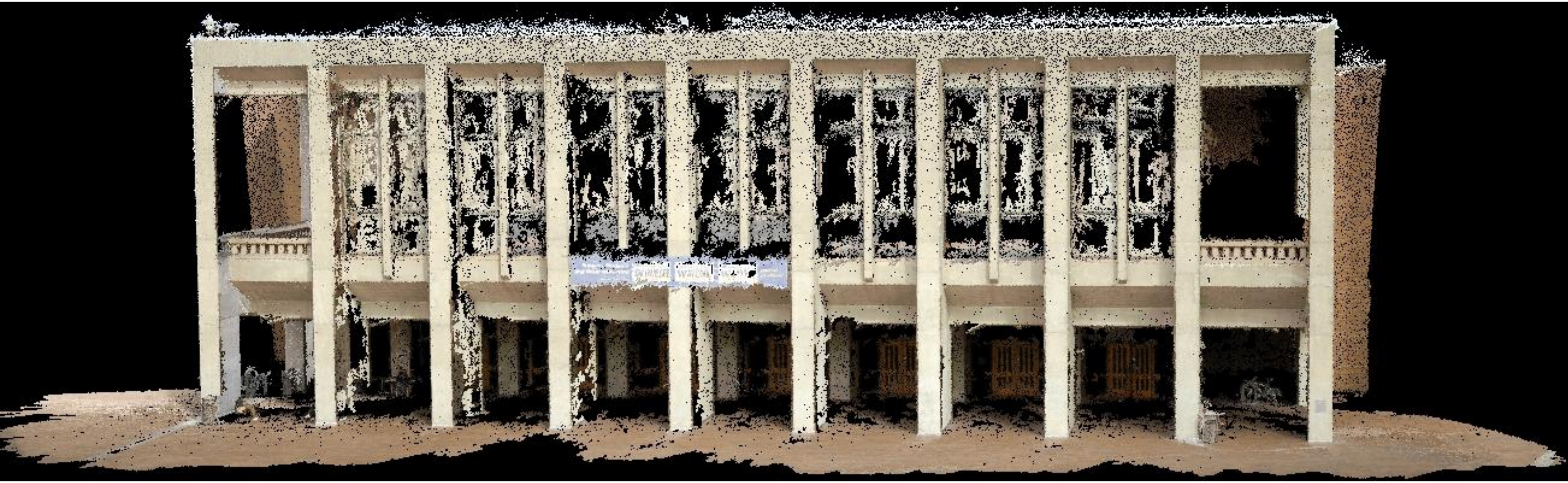
Third filter: Check if patches have some neighbors in reference and other images.

In one slide :)

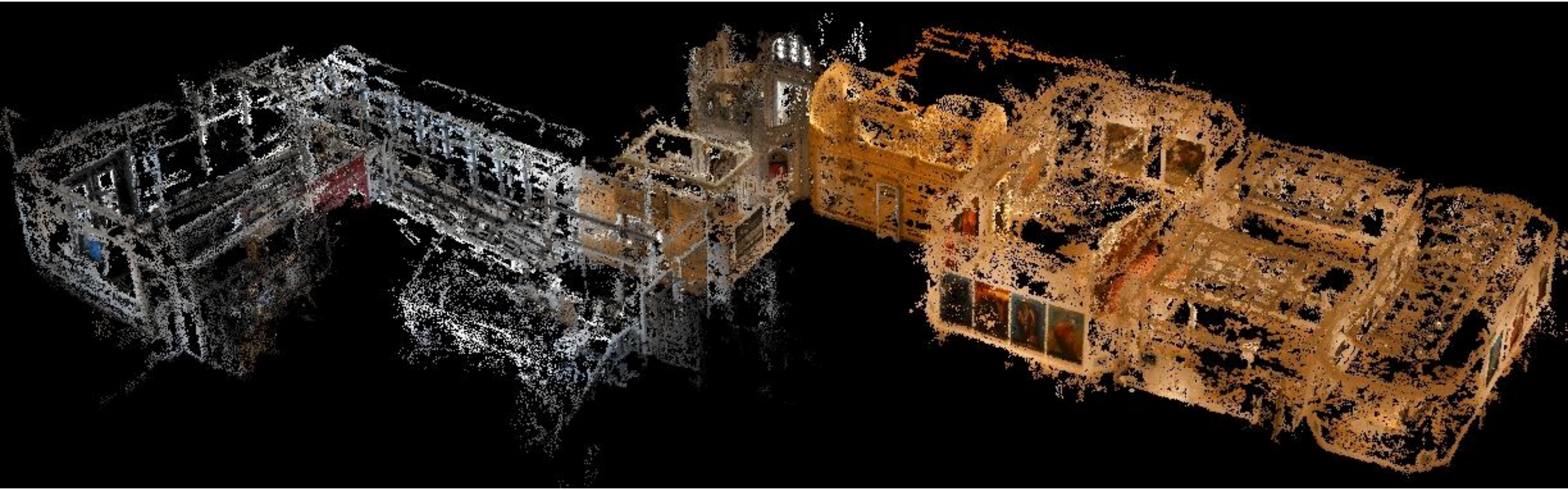
1. Detect keypoints
2. Triangulate a sparse set of initial matches
3. Iteratively expand matches to nearby locations
4. Use visibility constraints to filter out false matches
5. Perform surface reconstruction

Results

Results



Results



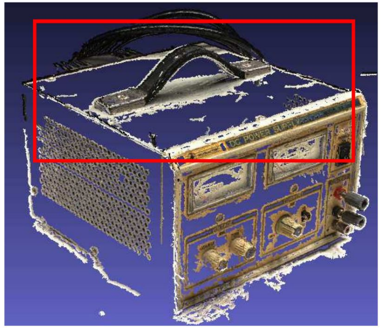
VisualSFM+PMVS

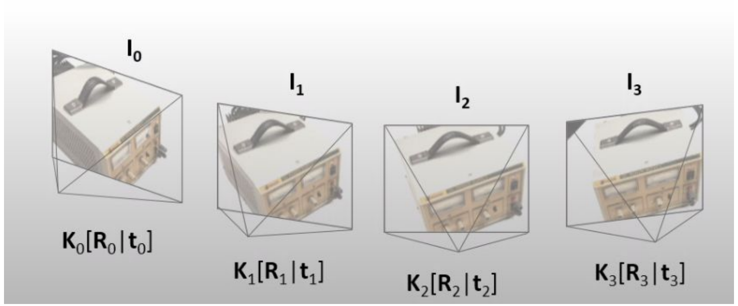
MVSNet: Depth Inference for Unstructured Multi-view Stereo

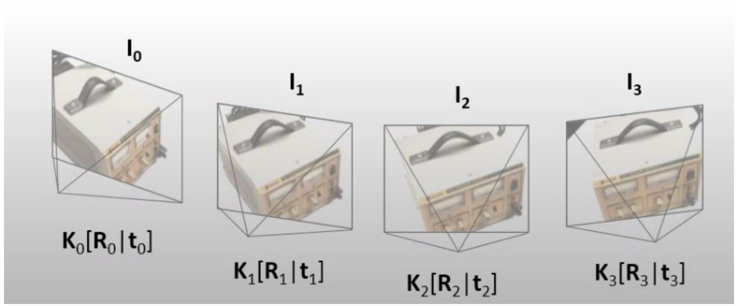
Authors: Yao Yao , Zixin Luo , Shiwei Li , Tian Fang , and Long Quan
Presenter: Nail Ibrahimli

PMVS x MVSNet

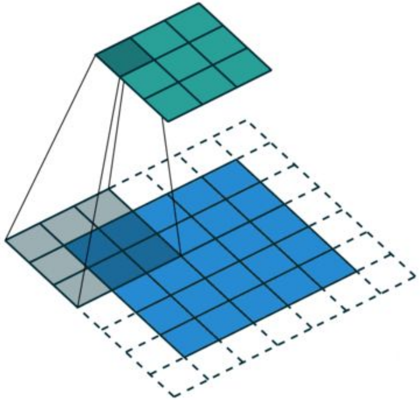
Textureless
Non-lambertian areas

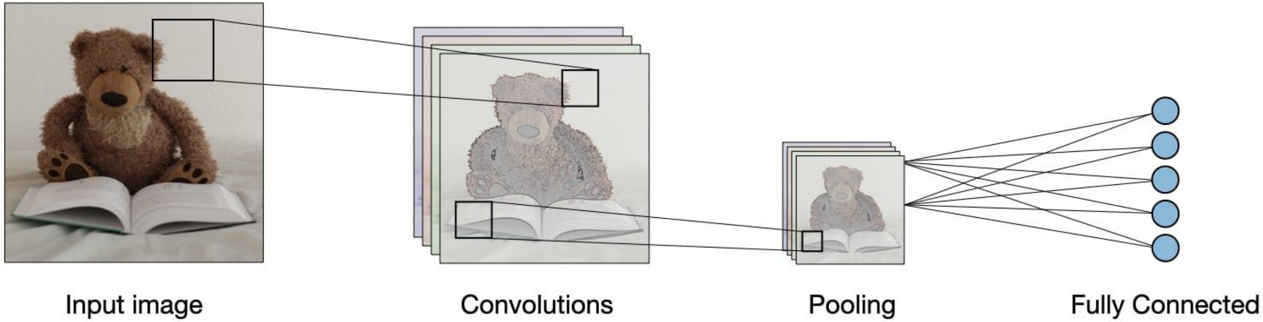


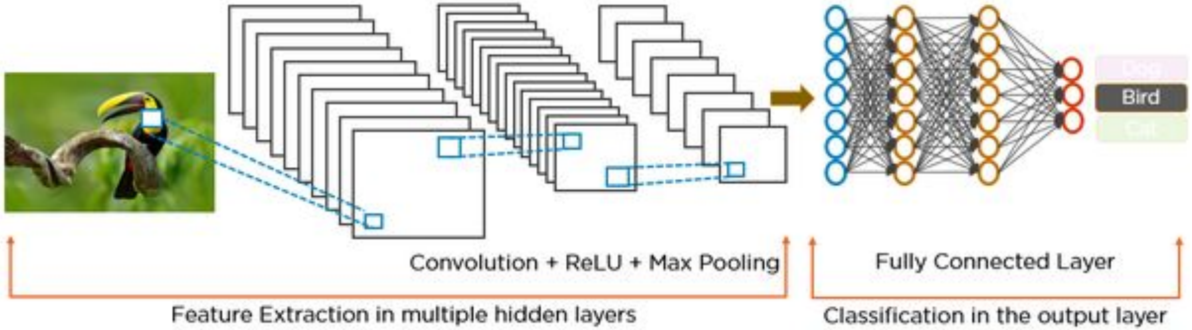




2D CNN: quick glance







3D CNN: quick glance

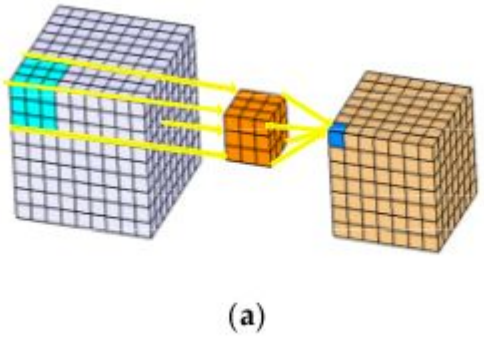
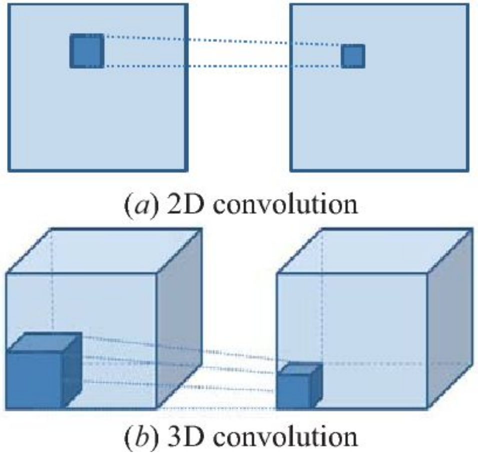
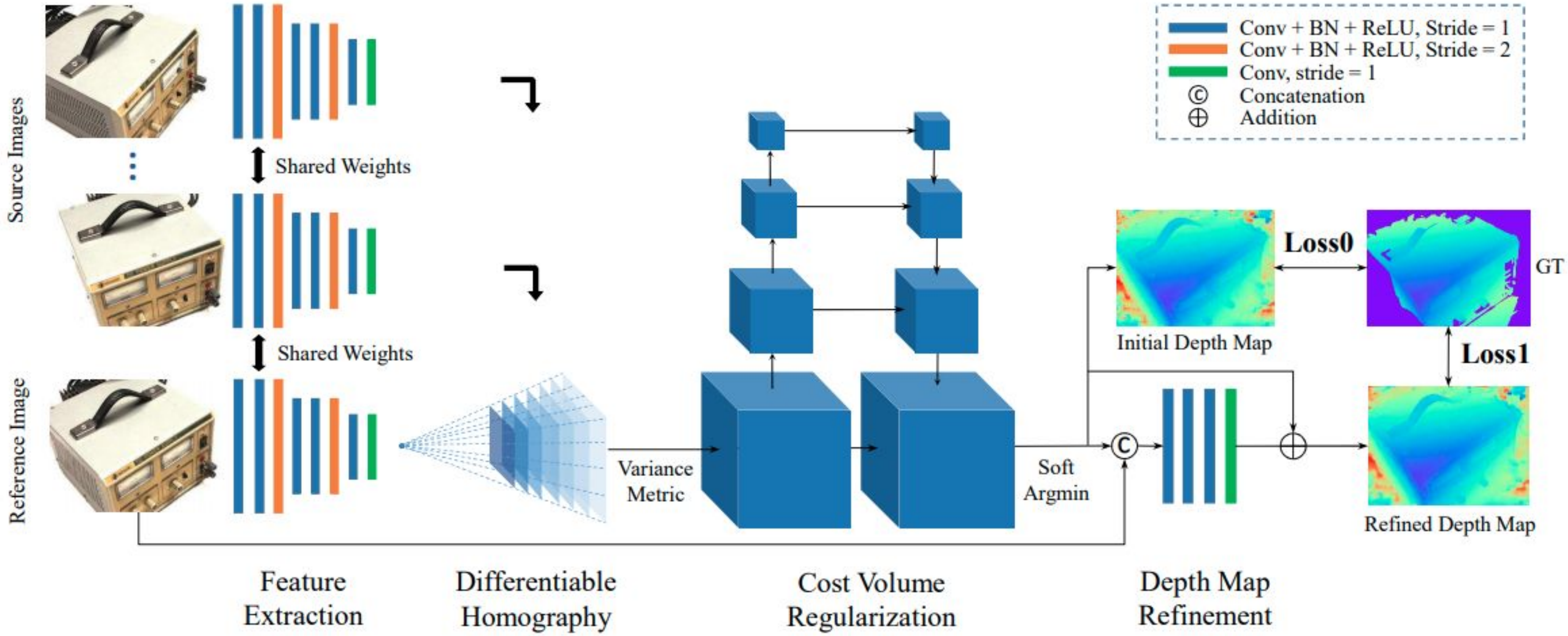


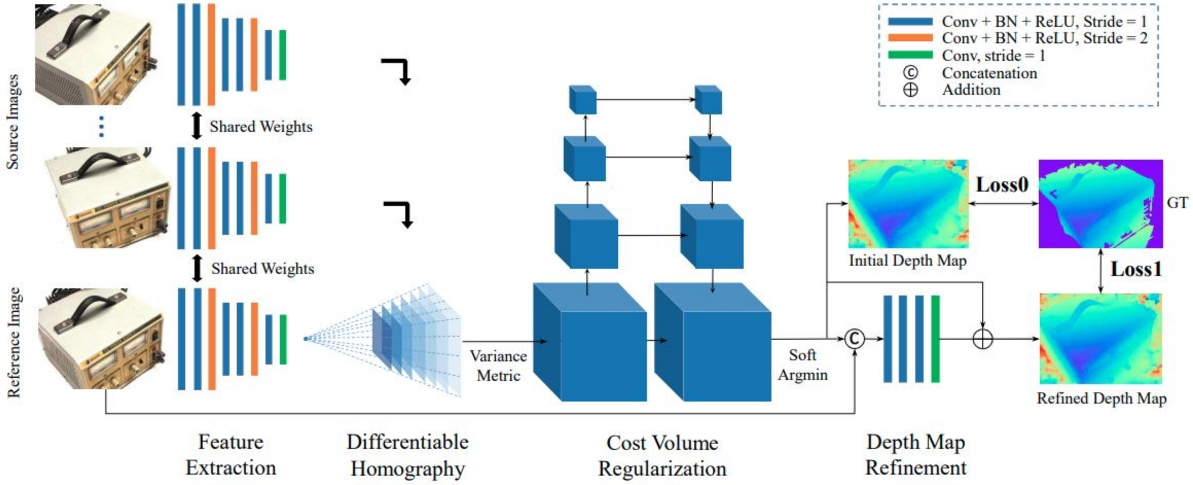
Figure 3. Illustration of 3D convolution: (**a**) illustration of a 3D kernel to extract spatial-spectral features; (**b**) illustration of multiple 3D kernels to extract different kinds of spatial-spectral local feature patterns.



MVSNET Architecture



MVSNET



End-to-end MVS learning framework

Camera geometry encoded as differentiable homography

Variance based cost metric

Image features

8 convolutional layers

32 channel pixel descriptor

$$Images\ \{I_i\}_{\{i=1\}}^{N} \xrightarrow{\text{2D CNN}} Deep\ Features\ \{F_i\}_{\{i=1\}}^{N}$$

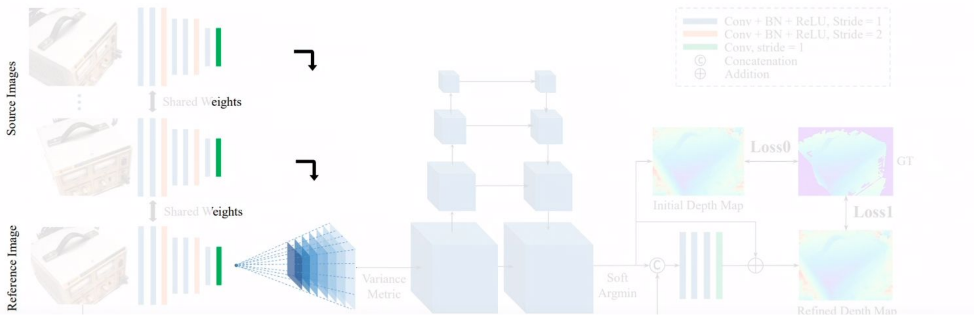
Differentiable homography warping

Use intrinsic/extrinsic parameters

Warp features to the Feature volumes

Volume dimension W/4xH/4xDxF

There are N feature Volumes



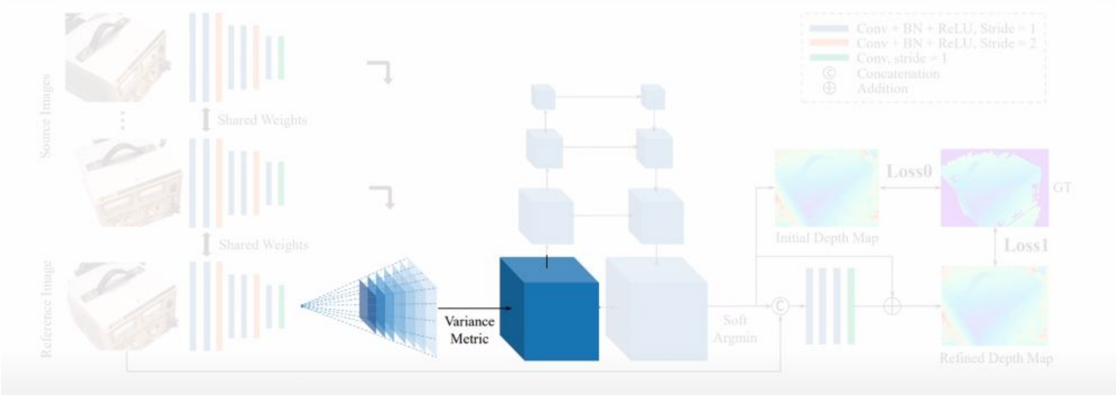
$$\textit{Deep Features } \{F_i\}_{\{i=1\}}^{N} \xrightarrow{\textit{Projection Parameters}} \textit{Feature Volumes } \{V_i\}_{\{i=1\}}^{N}$$

$$\mathbf{H}_i(d) = \mathbf{K}_i \cdot \mathbf{R}_i \cdot \left(\mathbf{I} - \frac{(\mathbf{t}_1 - \mathbf{t}_i) \cdot \mathbf{n}_1^T}{d}\right) \cdot \mathbf{R}_1^T \cdot \mathbf{K}_1^T$$

Cost Volume

Calculate the element wise cost of feature volumes

Dimension W/4xH/4xDxF



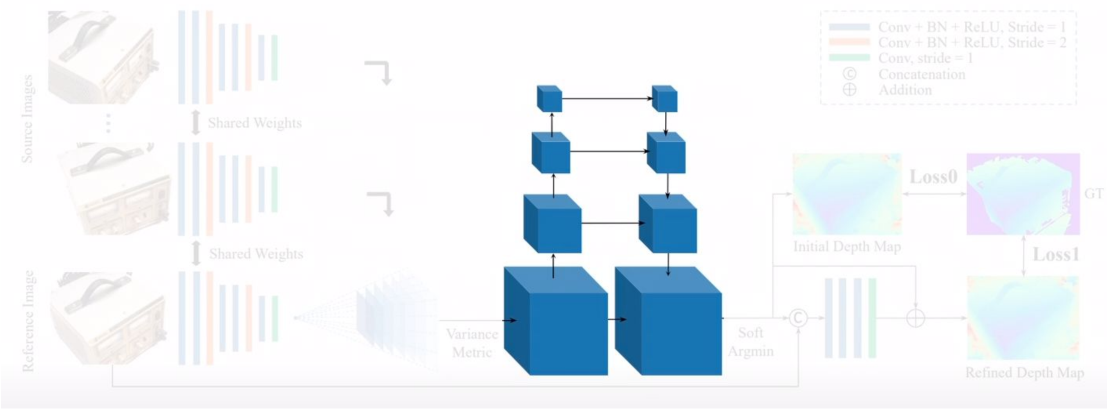
$$\textit{Feature Volumes } \{V_i\}_{\{i=1\}}^{N} \xrightarrow{\textit{Variance}} \textit{Cost Volume } \mathbf{C}$$

$$\mathbf{C} = \mathcal{M}(\mathbf{V}_1, \cdots, \mathbf{V}_N) = \frac{\sum_{i=1}^{N} (\mathbf{V}_i - \overline{\mathbf{V}_i})^2}{N}$$

Cost Volume Regularization

3D Unet Architecture

Initial dimension W/4xH/4xDxF

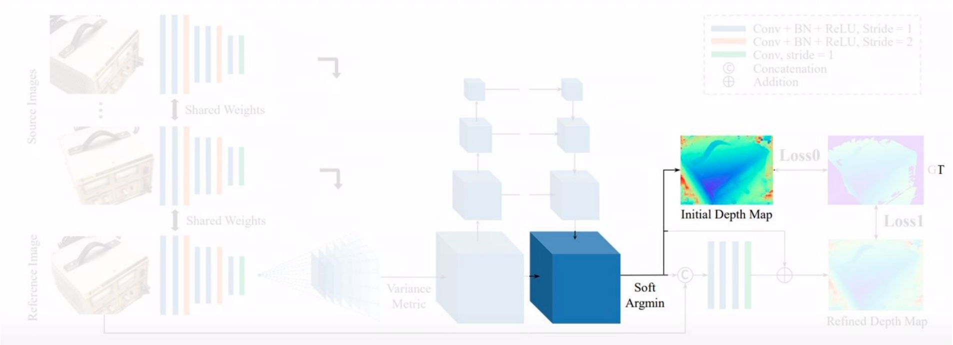


$$\textit{Cost Volume } \mathbf{C} \xrightarrow{\text{3D CNN}} \textit{Probability Volume } \mathbf{P}$$

Depth Map regression

Regressed depth based on expected value

Dimension W/4xH/4xD -> W/4xH/4

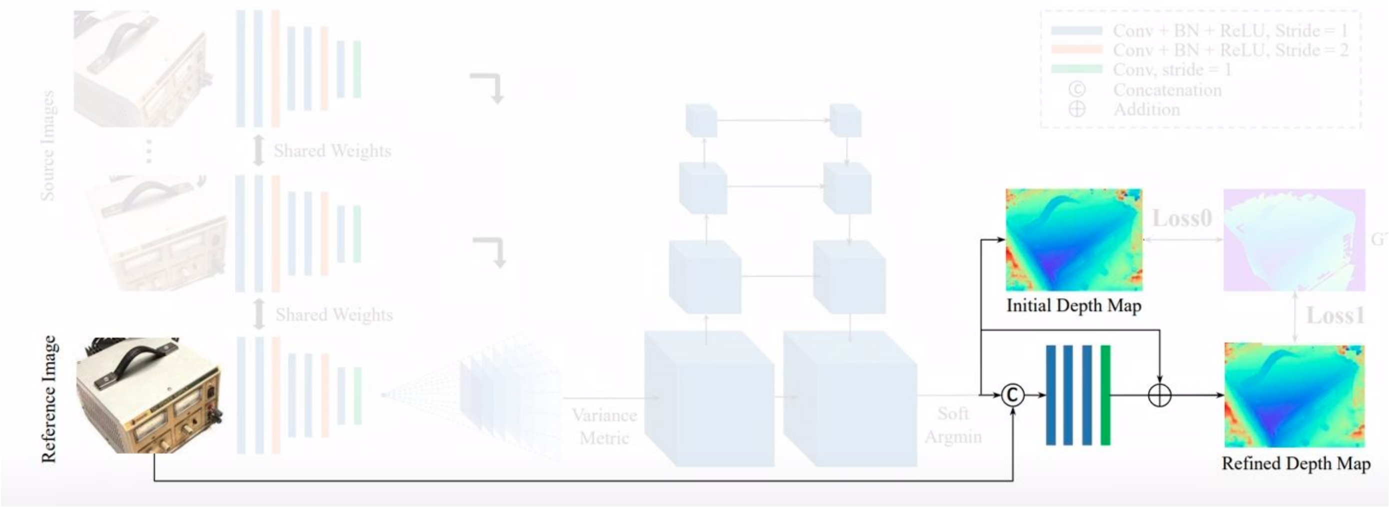


$$\textit{Probability Volume } \mathbf{P} \xrightarrow{\textit{Expectation value}} \textit{Depth Map } \mathbf{D}$$

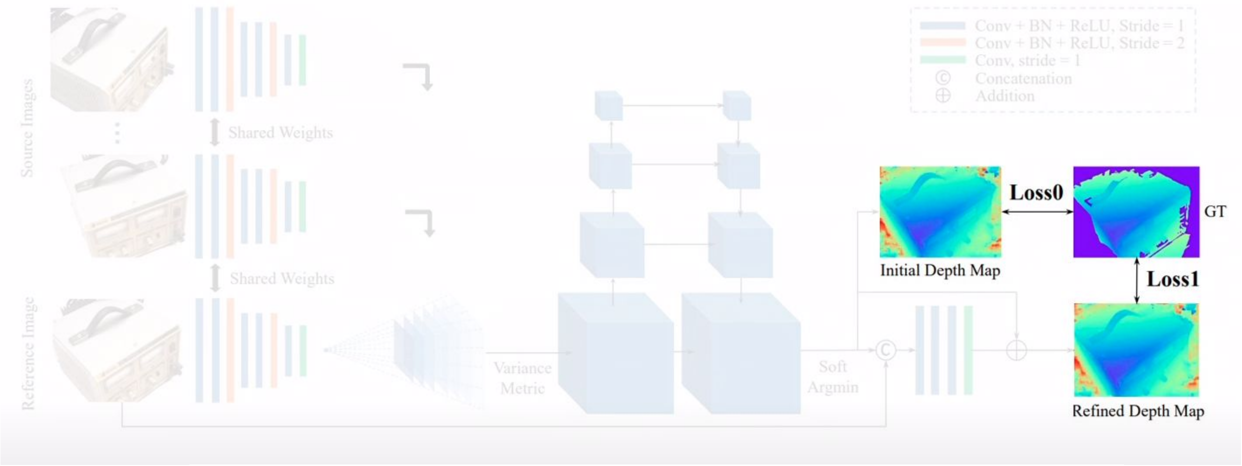
$$\mathbf{D} = \sum_{d=d_{min}}^{d_{max}} d \times \mathbf{P}(d)$$

Refine Depth map

$$D \xrightarrow{2D\ CNN} D_{refine}$$

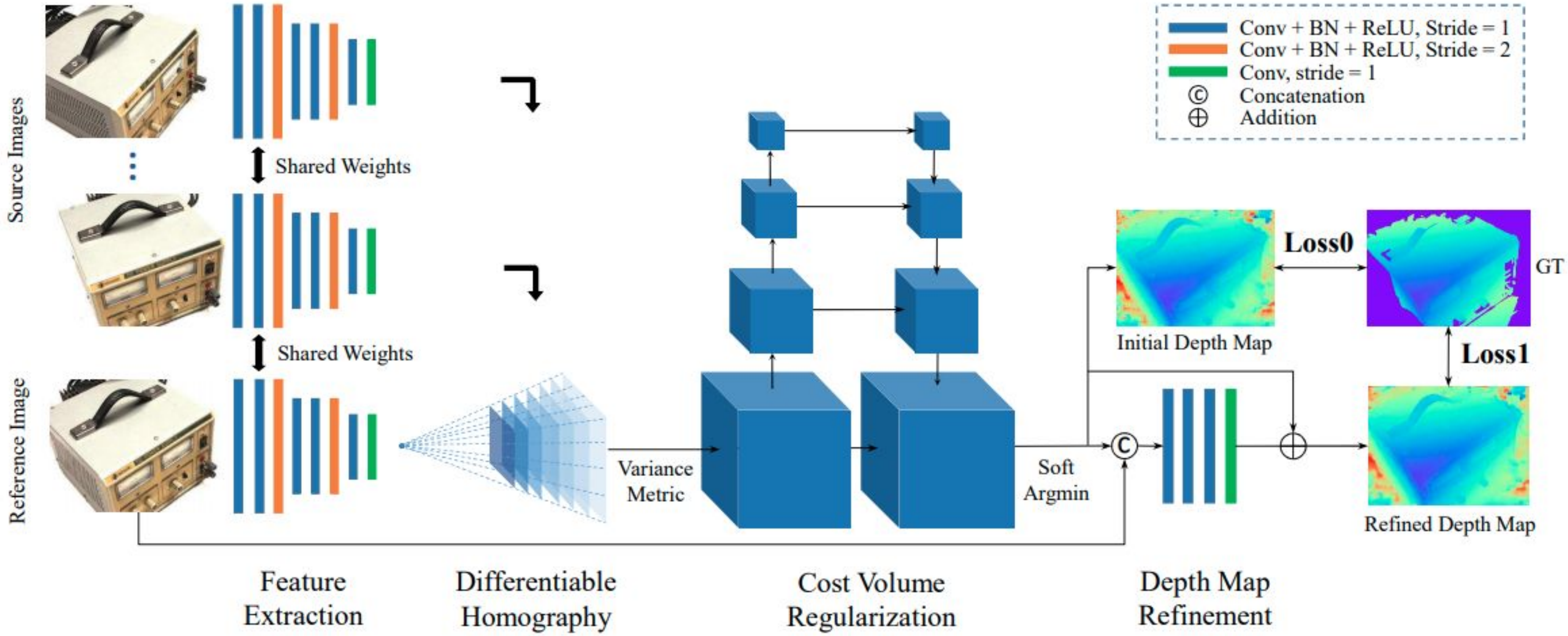


Loss



$$Loss = \sum_{p \in \mathbf{p}_{valid}} \underbrace{\|d(p) - \hat{d}_i(p)\|_1}_{Loss0} + \lambda \cdot \underbrace{\|d(p) - \hat{d}_r(p)\|_1}_{Loss1}$$

MVSNET Architecture



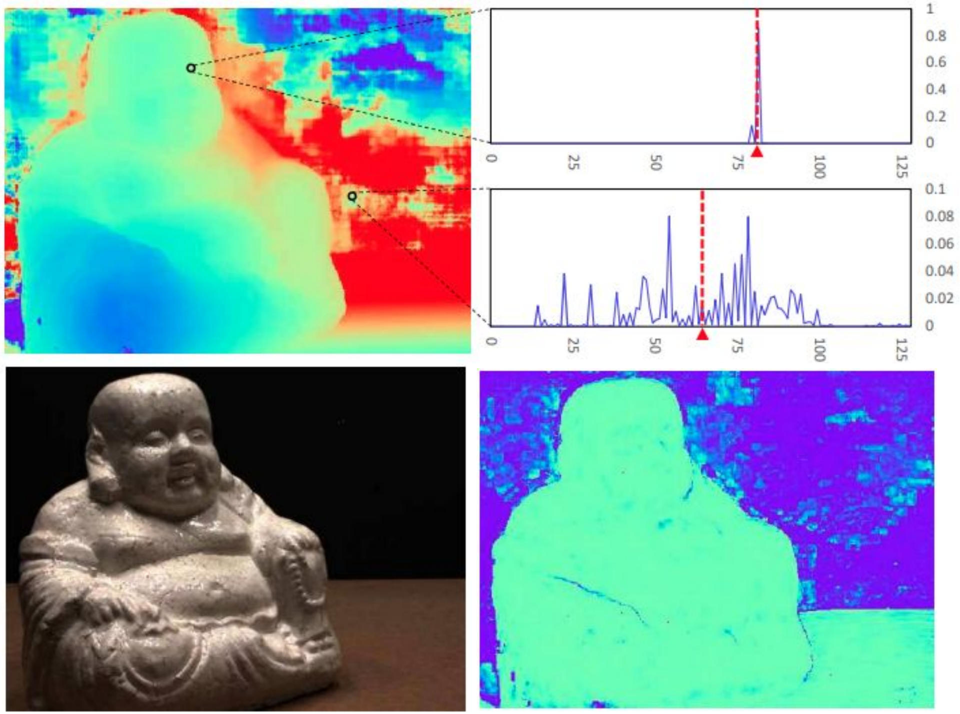
Filtering

Photometric filtering:

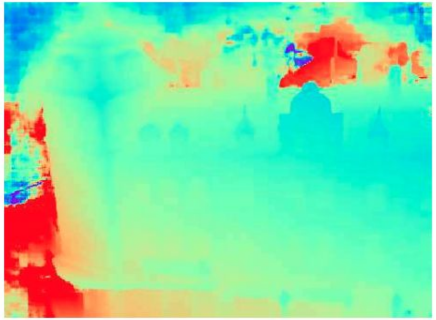
P(d)>0.8

Geometric filtering:

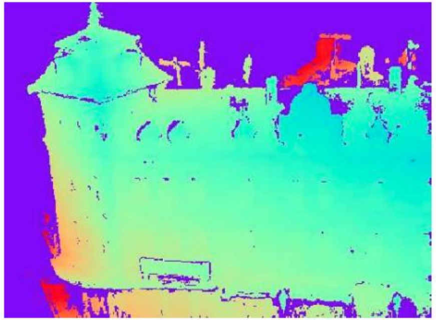
3 View visible



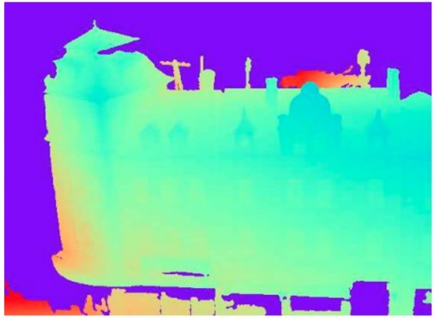
Filtering



(a) Inferred depth map



(b) Filtered depth map



(c) GT depth map

(d) Reference image

(e) Fused point cloud

(f) GT point cloud

Results


easy3D
Rendering (Hz): 44


easy3D
Rendering (Hz): 48


easy3D
Rendering (Hz): 60


easy3D
Rendering (Hz): 25


easy3D
Rendering (Hz): 50