# GC-MVSNet: Multi-View, Multi-Scale, Geometrically-Consistent Multi-View Stereo

Vibhas K. Vats [1] Sripad Joshi [1] David J. Crandall [1] Md. Alimoor Reza [2] Soon-Heung Jung [3]

[1]Indiana University, Bloomington, Indiana [2]Drake University, Des Moines, Iowa [3]Electronics and Telecommunications Research Institute, Korea

## Multi-View Stereo Problems

- Depth map-based MVS algorithms estimate the reference view depth maps using multiple RGB inputs (Reference + Source views)
- A consistent scene requires geometric consistency of depth estimates across multiple views

Two broader approaches are undertaken to ensure geometric consistency in estimated depth maps:

- Repeated application of geometric constraints during the depth estimation process → Traditional MVS Algorithms
- Geometric constraints applied as a post-processing step → Learning-based MVS Algorithms

GC-MVSNet is a learning-based algorithm with geometric constraints applied during the learning process.

## Learning-Based MVS Algorithms

A learning-based MVS method:

- Extract multi-level features using CNNs
- Creates a matching 3D cost volume using features
- Regularize cost volume using 3D-CNN
- Filter geometrically consistent points to generate 3D point-cloud

They only use Geometric Constraints as a post-processing step for filtering multi-view consistent points. It leads to:

- Limited geometric cues during the learning process
- Require more training iterations to learn to reason about geometry

## Hypothesis

### GC-MVSNet:

- Explicitly models cross-view geometric constraints during learning
- It penalizes geometrically inconsistent estimates during learning

With such explicit geometric constraint modeling, GC-MVSNet should:

- Develop a better understanding of multi-view geometry → Improved quantitative results
- Learn quickly to reason about scene geometry → Require less training iterations

## Forward-Backward-Reprojection

**Inputs:** $D_0, c_0, D_i^{gt}, c_i^{gt}$
**Output:** $D''_{P''_0}, P''_0$

$K_R, E_R \leftarrow c_0;\ K_S, E_S \leftarrow c_i^{gt}$

$D_{(R\rightarrow S)} \leftarrow K_S \cdot E_S \cdot E_R^{-1} \cdot K_R^{-1} \cdot D_0$ ▷ Project

$X_{D_{(R\rightarrow S)}}, Y_{D_{(R\rightarrow S)}} \leftarrow D_{(R\rightarrow S)}$

$D_{S_{remap}} \leftarrow REMAP(D_i^{gt}, X_{D_{(R\rightarrow S)}}, Y_{D_{(R\rightarrow S)}})$ ▷ Remap

$D''_{P''_0} \leftarrow K_R \cdot E_R \cdot E_S^{-1} \cdot K_S^{-1} \cdot D_{S_{remap}}$ ▷ Back project

$P''_0 \leftarrow (X_{D''_{P''_0}}, Y_{D''_{P''_0}})$

## Other Modifications

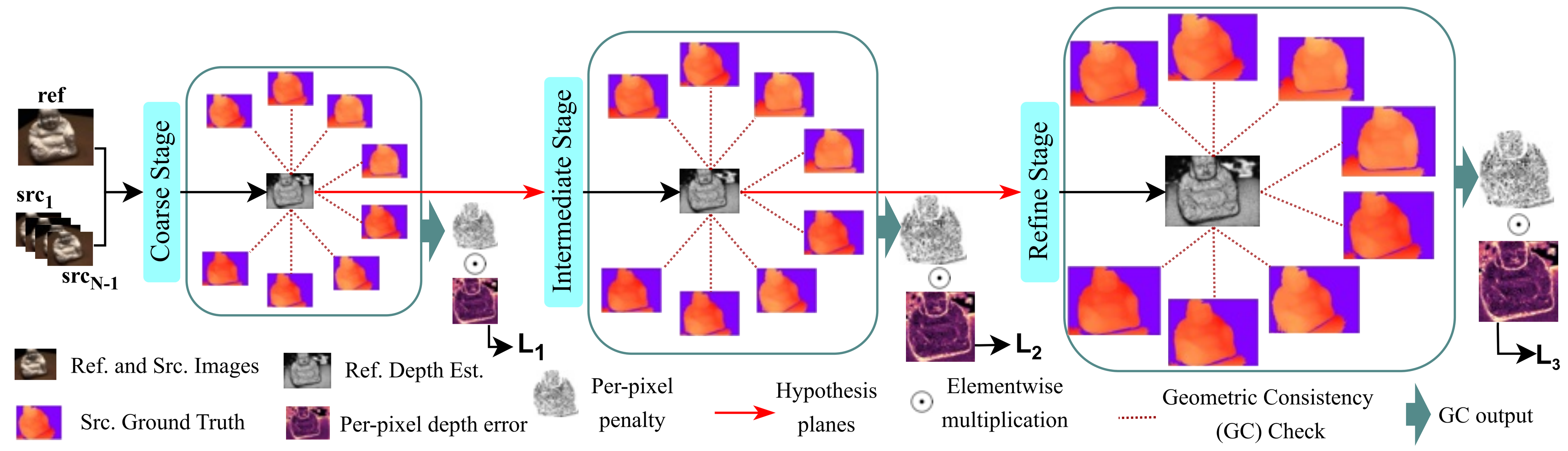
Two additional modifications were to stabilize the model's performance.

- Keeping the feature-extraction-network as Feature Pyramid Network, replaced the regular conv-layers with deformable conv-layers
- Replaced BatchNorm-layers with GroupNorm-layers as BatchNorm is not well suited for small batch-size

## Method

### Geometric-Consistency (GC) Module:

- Applied at the end of each stage to check cross-view consistency of the reference view depth maps
- Generates penalty for geometrically inconsistent estimates for each stage




## Geometric-Consistency Module

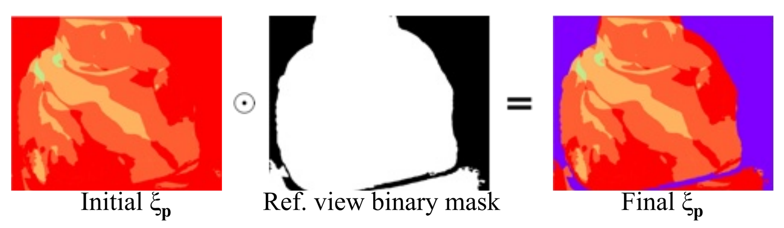
### Complete GC-Algorithm

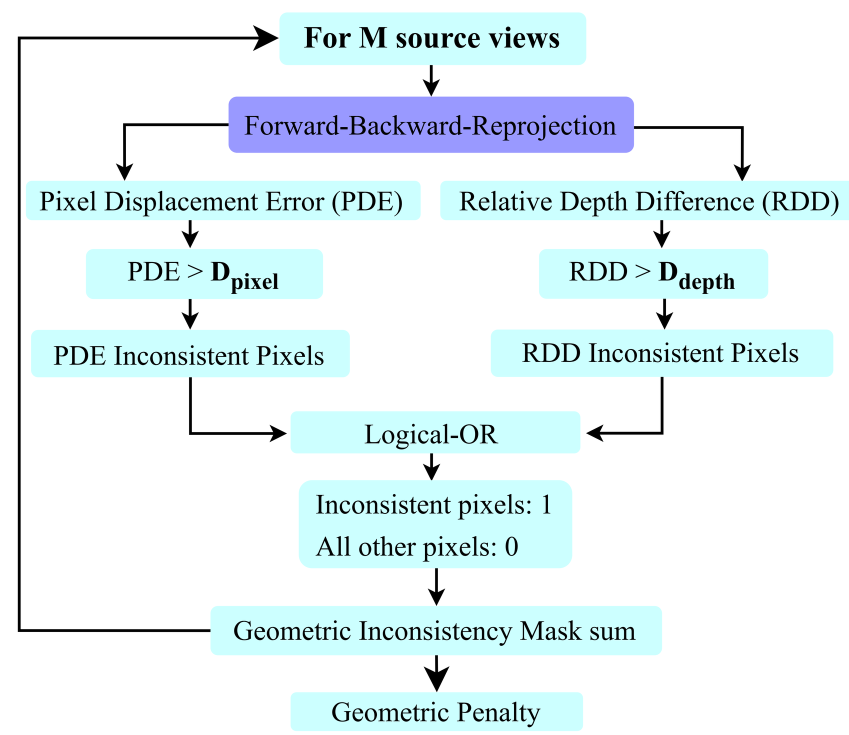
Initialize Mask-Sum → 0

For each Src. depth map:

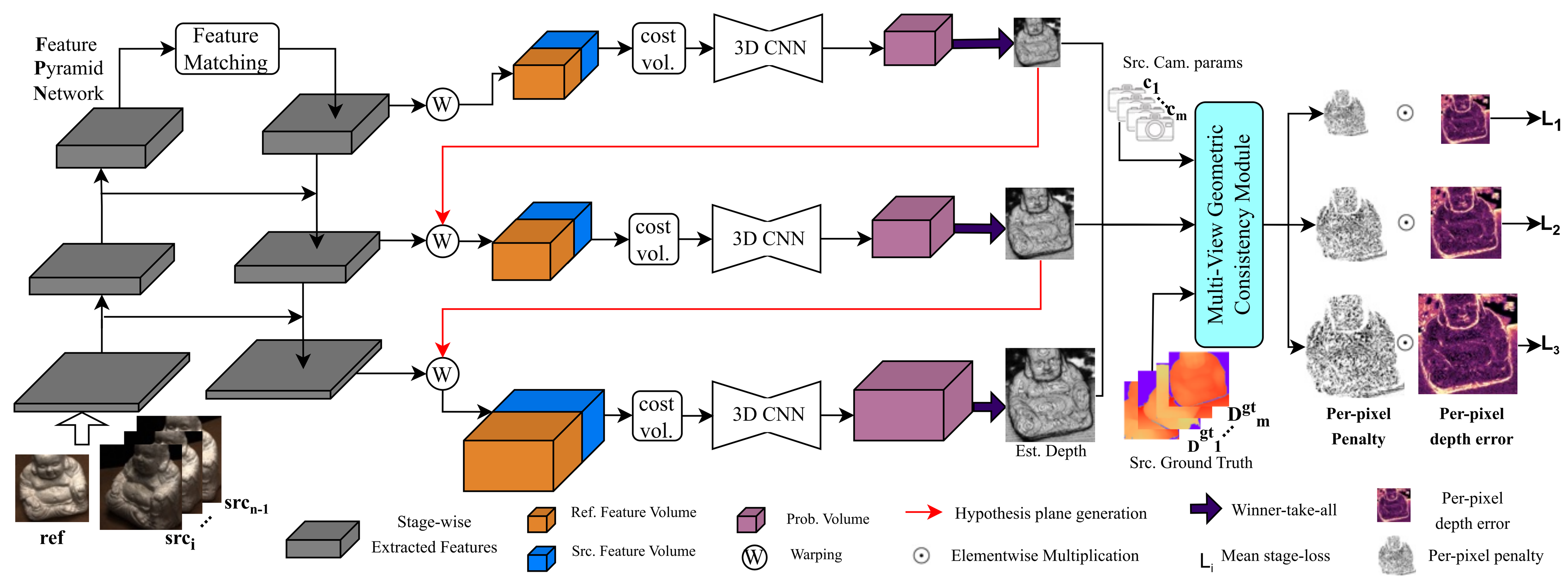
1. forward-backward-reprojection to get PDE and RDD
   - PDE $\leftarrow ||P_0 - P''_0||_2$
   - RDD $\leftarrow {}^1/_{D_0}||D''_{P''_0} - D_0||_1$
2. Select geometrically inconsistent pixels
   - $PDE_{mask} > D_{pixel}$
   - $RDD_{mask} > D_{depth}$
3. Combine inconsistent pixels from both masks
   - Logical-OR $(PDE_{mask}, RDD_{mask})$
4. Current-Mask ← Assign penalty to each pixel
   - Inconsistent pixels → 1
   - All other pixels → 0
5. Add Current-Mask to initial Mask-Sum

Geometric penalty ($\xi_p$) ← average Mask-Sum
Apply reference view binary mask to generate final $\xi_p$




## GC-MVSNet Architecture




## Quantitative Result on DTU Dataset

| | Method | Acc ↓ | Comp ↓ | Overall ↓ |
|---|---|---|---|---|
| Traditional | Furu [9] | 0.613 | 0.941 | 0.777 |
| | Tola [36] | 0.342 | 1.190 | 0.766 |
| | Gipuma [10] | **0.283** | 0.873 | 0.578 |
| | COLMAP [33] | 0.400 | 0.664 | 0.532 |
| Learning-based | SurfaceNet [16] | 0.450 | 1.040 | 0.745 |
| | MVSNet [48] | 0.396 | 0.527 | 0.462 |
| | P-MVSNet [25] | 0.406 | 0.434 | 0.420 |
| | R-MVSNet [49] | 0.383 | 0.452 | 0.417 |
| | Point-MVSNet [2] | 0.342 | 0.411 | 0.376 |
| | CasMVSNet [12] | 0.325 | 0.385 | 0.355 |
| | CVP-MVSNet [47] | 0.296 | 0.406 | 0.351 |
| | UCS-Net [3] | 0.338 | 0.349 | 0.344 |
| | AA-RMVSNet [41] | 0.376 | 0.339 | 0.357 |
| | UniMVSNet [30] | 0.352 | 0.278 | 0.315 |
| | TransMVSNet [6] | 0.321 | 0.289 | 0.305 |
| | GBi-Net* [28] | 0.312 | 0.293 | 0.303 |
| | MVSTER [39] | 0.350 | 0.276 | 0.313 |
| | **GC-MVSNet** (ours) | 0.330 | **0.260** | **0.295** |
| | GBi-Net [28] | 0.315 | 0.262 | 0.289 |
| | **GC-MVSNet** (ours) | 0.323 | **0.255** | 0.289 |

Our method achieve State-of-the-art result on two datasets:

- DTU and BlendedMVS

## GC: A Plug-in Module

GC module is designed as a plug-in module

- Plug into any depth map-based MVS method
- Retraining the network with GC-module provides:
  - Improved quantitative results to its previous performance
  - Require less training iterations to achieve optimal performance

We demonstrate this on two different methods:

- CasMVSNet and TransMVSNet

| Methods | Loss | Other | GC | Overall↓ | Epoch |
|---|---|---|---|---|---|
| CasMVSNet [2] | $L_1$ | × | × | 0.355 | 16 |
| | $L_1$ | ✓ | × | 0.357 | 16 |
| | $L_1$ | × | ✓ | 0.335 | 11 |
| TransMVSNet [1] | FL | × | × | 0.305 | 16 |
| | FL | ✓ | × | 0.322 | 16 |
| | FL | × | ✓ | 0.303 | 8 |

Table 1. GC-module as a plug-in module in TransMVSNet and CasMVSNet

## References

[1] Yikang Ding, Wentao Yuan, Qingtian Zhu, Haotian Zhang, Xiangyue Liu, Yuanjiang Wang, and Xiao Liu. Transmvsnet: Global context-aware multi-view stereo network with transformers. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8585–8594, 2022.

[2] Xiaodong Gu, Zhiwen Fan, Siyu Zhu, Zuozhuo Dai, Feitong Tan, and Ping Tan. Cascade cost volume for high-resolution multi-view stereo and stereo matching. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 2495–2504, 2020.

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