MVSNet系列

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Multi-view stereo

MEGVII 旷视

多视角图像

↓

特征提取匹配

↓

稀疏重建SFM

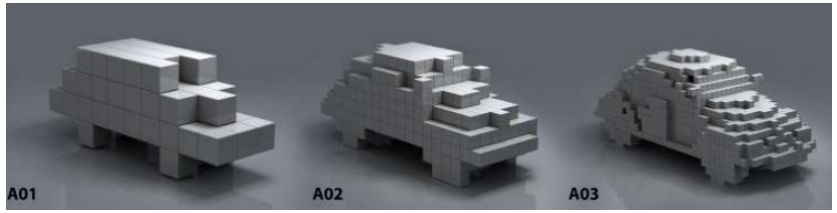
↓

稠密重建MVS

稠密重建MVS

基于体素

MVS等价为一个3D空间Voxel的标记问题

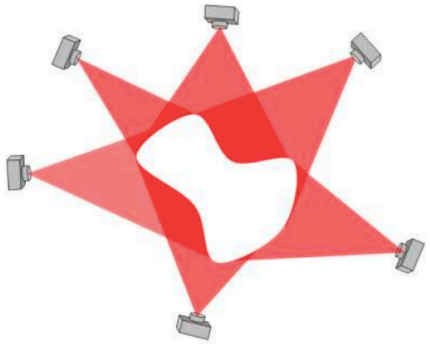


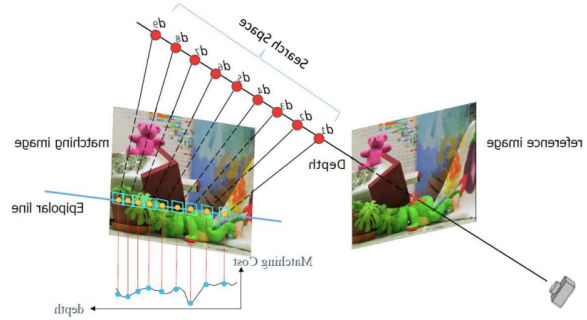
基于特征点扩散

利用特征点生成初始点云再扩散和过滤

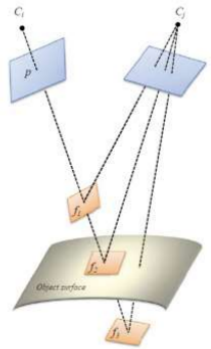
基于深度图融合

为每一幅图片选取立体图像对来计算每一幅图的深度再进行深度图的融合得到点云模型





depth



normal

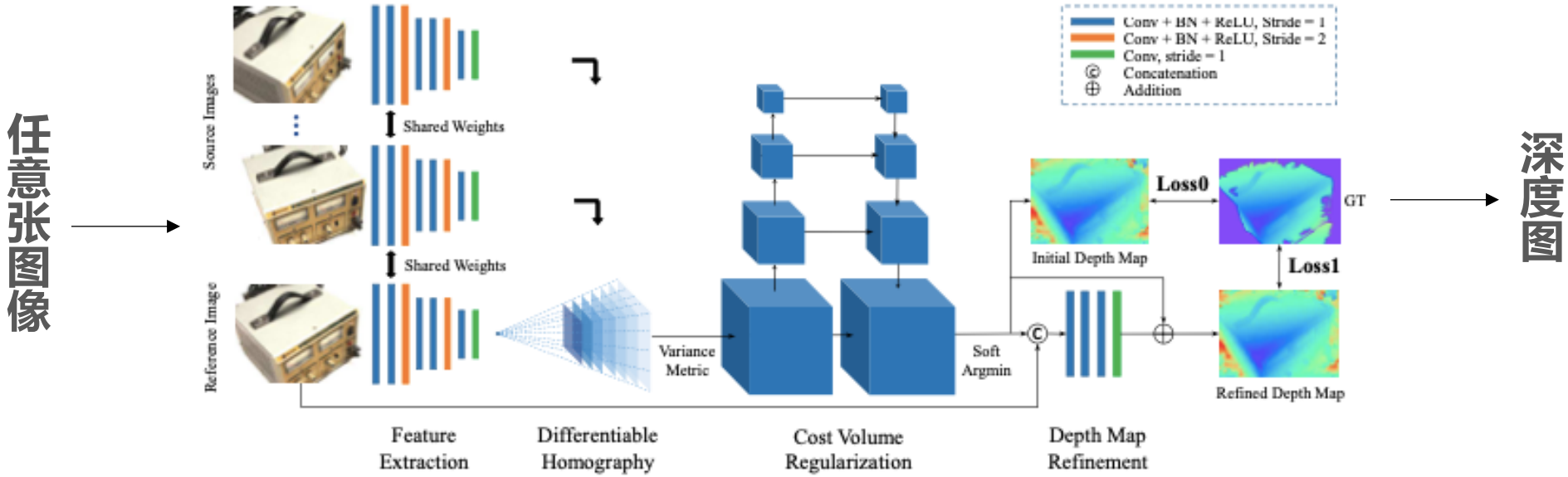
MVSNet

传统MVS 基于手工设计的相似性算法和鲁棒性矫正方法去计算稠密匹配并恢复3D点

虽然精度较高，但是由于弱纹理，镜面或者反射效应的表面的原因使得在大场景下的点云完整度待提高

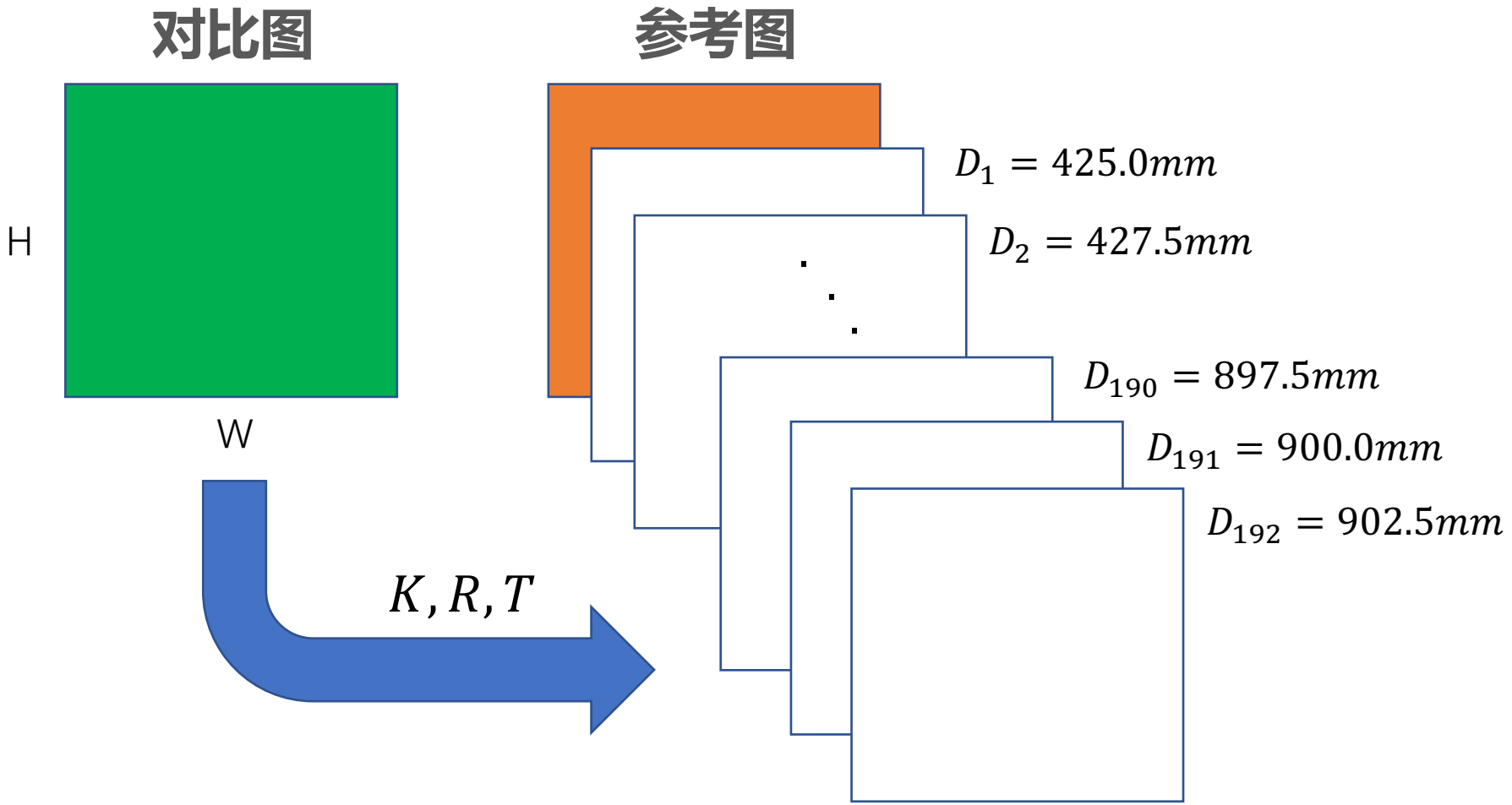
双目立体 双目图像对是矫正对齐过的图片，不用考虑相机参数，只需估计图像对水平方向上像素点的视差

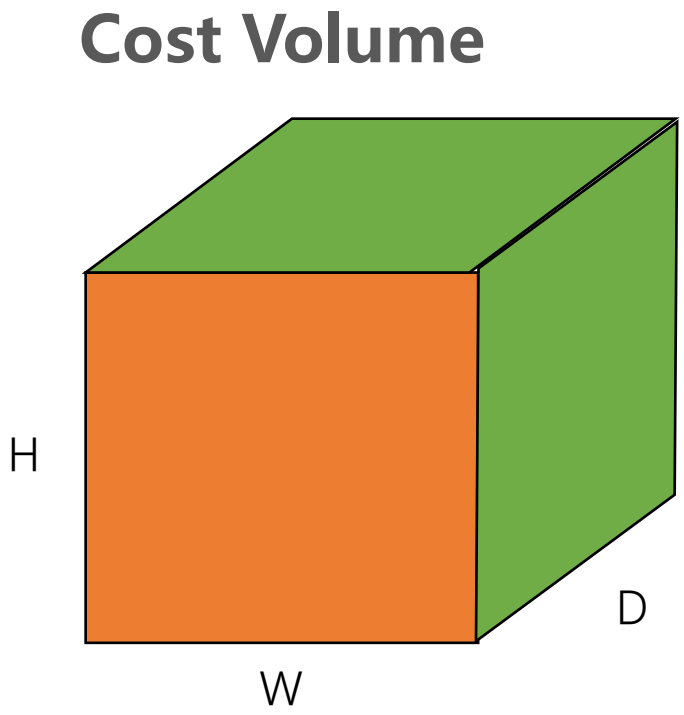
网络MVS 输入是任意位姿的多张图像，且多张图片之间的关系需要被整体考虑



Yao, Yao, Zixin Luo. MVSNet: Depth Inference for Unstructured Multi-view Stereo. ECCV (2018).

Homography Warping





耗费显存

$$H \times W \times D \times F = 1600 \times 1184 \times 192 \times 32 = 11\text{G}$$

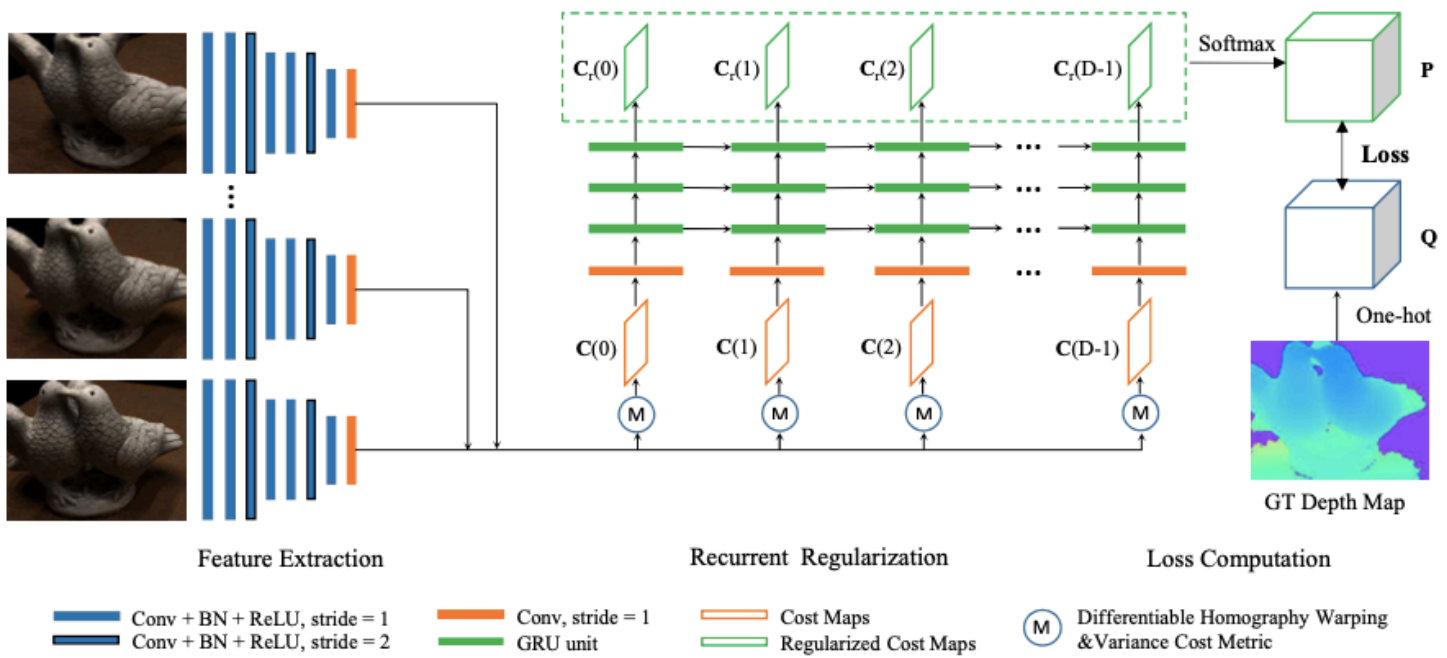
优点

1.在保证准确度的情况下，点云恢复**完整性**最好
2.运行速度是Gipuma的5倍，colmap的**100倍**

R-MVSNet

网络结构 门控循环单元代替了3D CNN去做cost volumn的Regularization

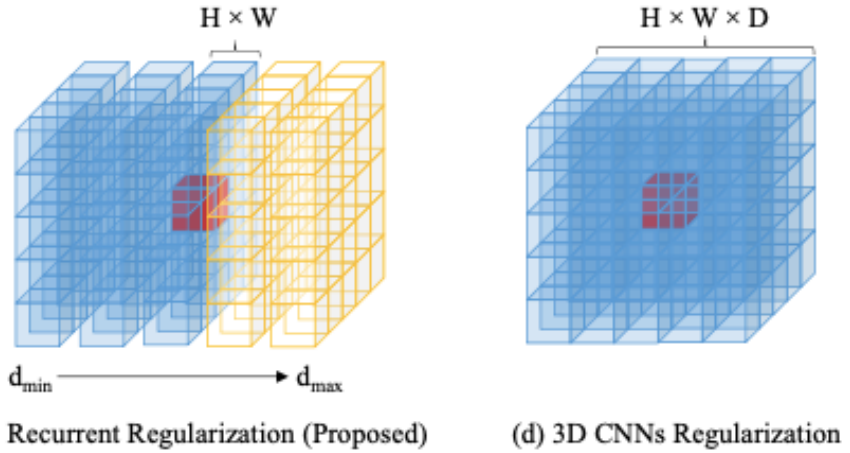
GRU可以更好地捕捉depth序列中depth相隔较大的整体关系



方法对比

3D CNN的方法占用的显存立方性增长

基于GRU的方法明显更节约显存



优点 低显存占用可以重建更大depth范围的场景和更高的重建精度, 且8倍效率相对于MVSNet

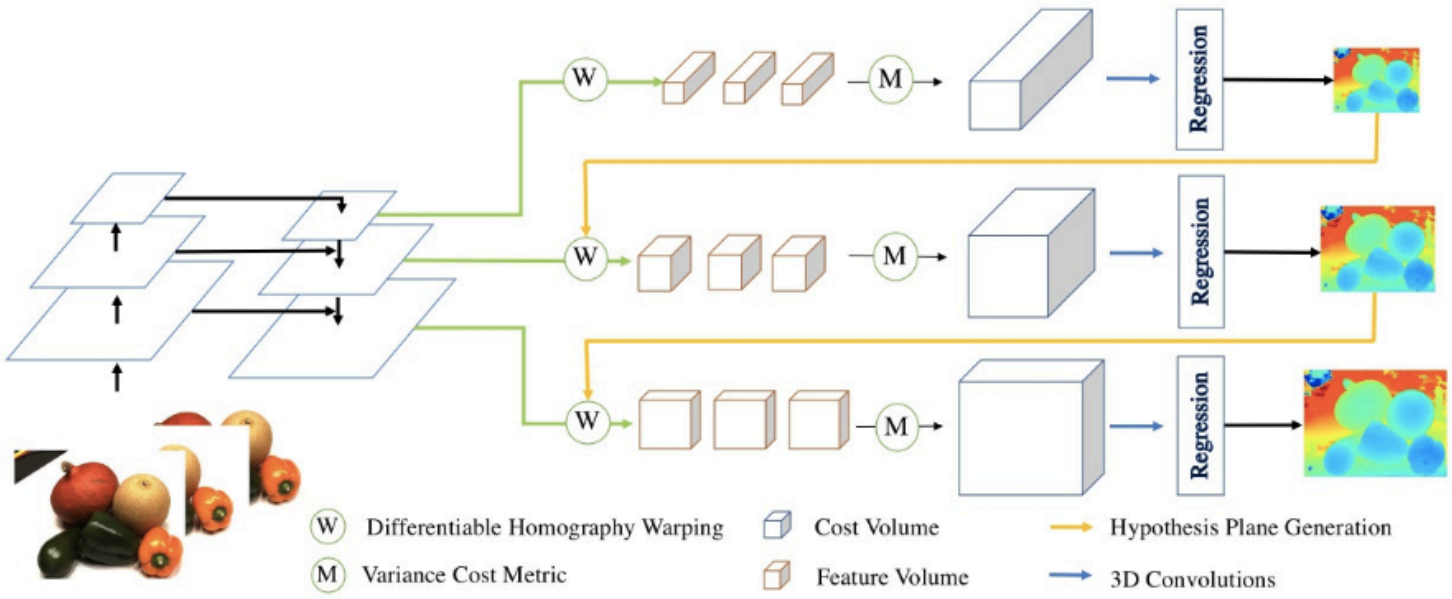
12G显存GPU最大可以处理分辨率为3072x2048的图像，胜任大多数的MVS数据集除了ETH3D的高分辨率数据集

Yao, Yao et al. Recurrent MVSNet for High-Resolution Multi-View Stereo Depth Inference. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2019): 5520-5529.

Cascade-MVSNet

网络结构 采用特征图像金字塔结构对不同尺度的特征进行编码

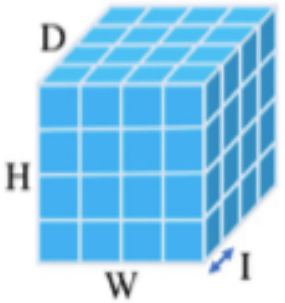
coarse-to-fine和thin adaptive volume



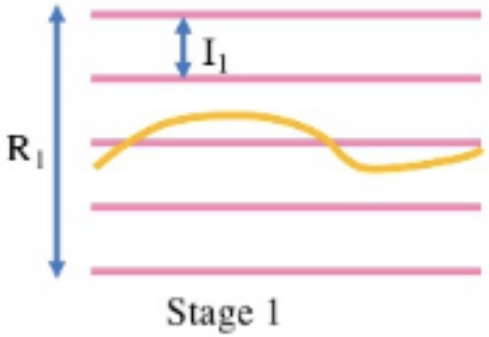
Coarse-to-Fine

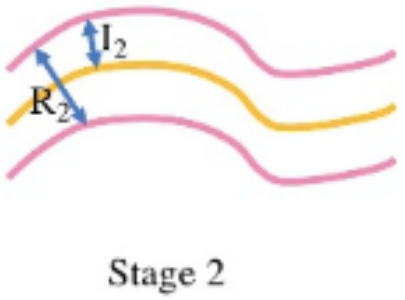
在步进的stage中，构造的cost volume：

- D的范围（R_1）会逐步变小
- 分辨率（I_1）会逐步变小



	Plane Num.	Plane Interv.	Spatial Res.
Efficiency	Negative	Positive	Negative
Accuracy	Positive	Negative	Positive





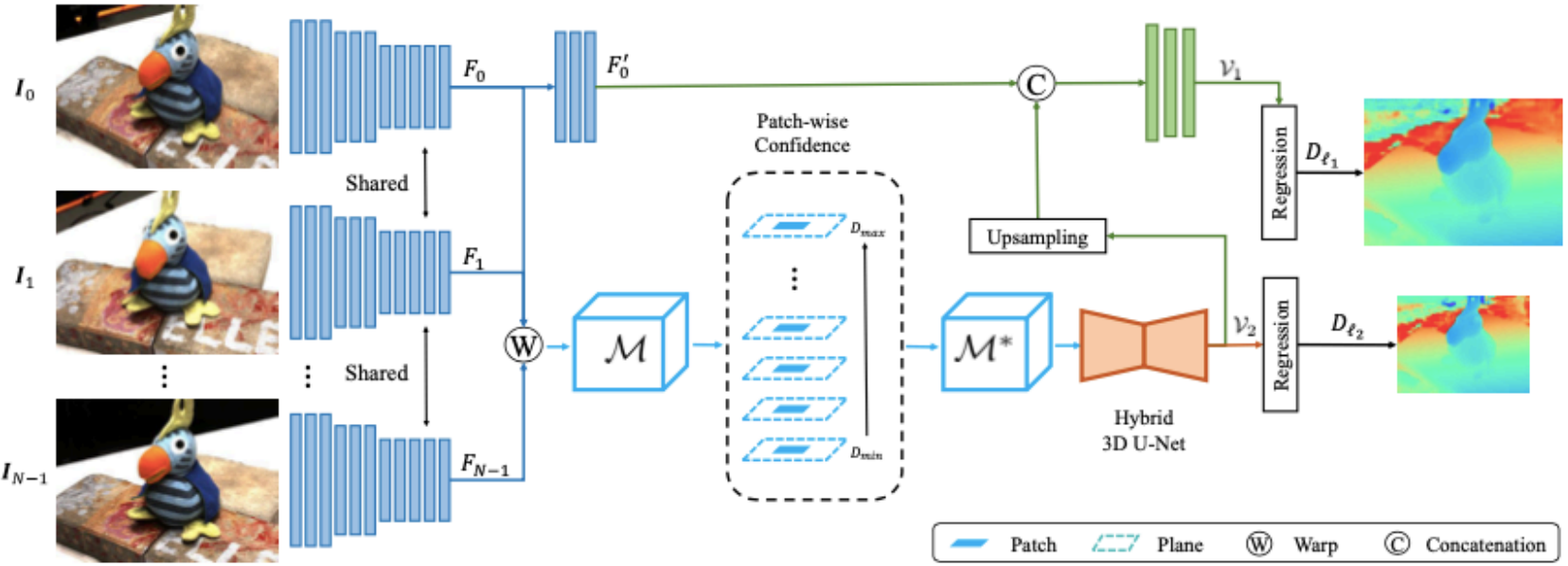
优点 50.6%的显存占用，59.3%的运行时间和23.1%的精度提高相对于MVSNet

1. Gu, X., Fan, Z., Zhu, S., Dai, Z., Tan, F., & Tan, P. (2019). Cascade Cost Volume for High-Resolution Multi-View Stereo and Stereo Matching. ArXiv, abs/1912.06378.
2. Cheng, S., Xu, Z., Zhu, S., Li, Z., Li, E.L., Ramamoorthi, R., & Su, H. (2019). Deep Stereo using Adaptive Thin Volume Representation with Uncertainty Awareness. ArXiv, abs/1911.12012.

P-MVSNet

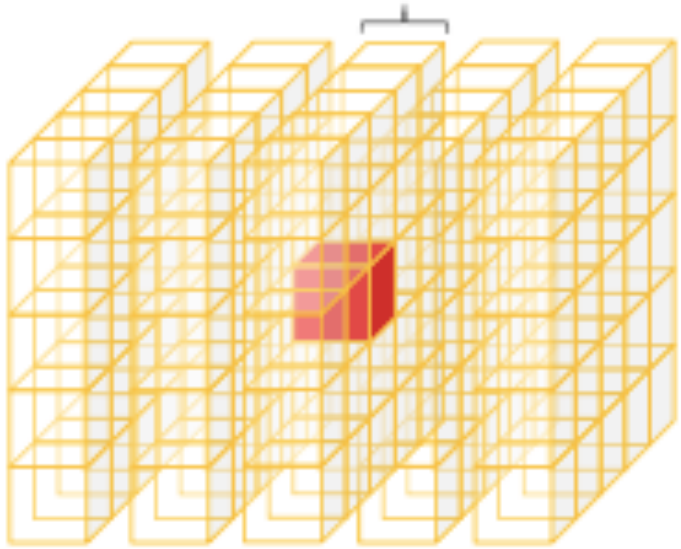
网络结构 从pixel-wise拓展到patch-wise cost volume

Hybrid 3D U-Net + depth修正高分辨率输出



Pixel-wise

Patch-wise比pixel-wise提高了匹配的精度和鲁棒性

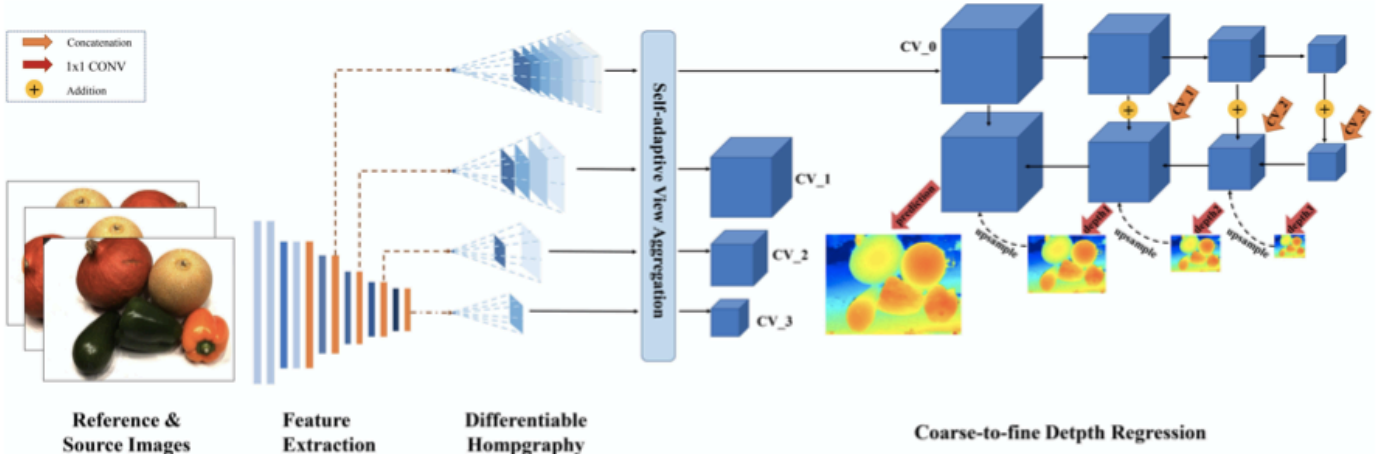


特点 借用了mvs中的patch-match的思想，使得depth和重建的点云的准确性和完整性都提高了

PVA-MVSNet

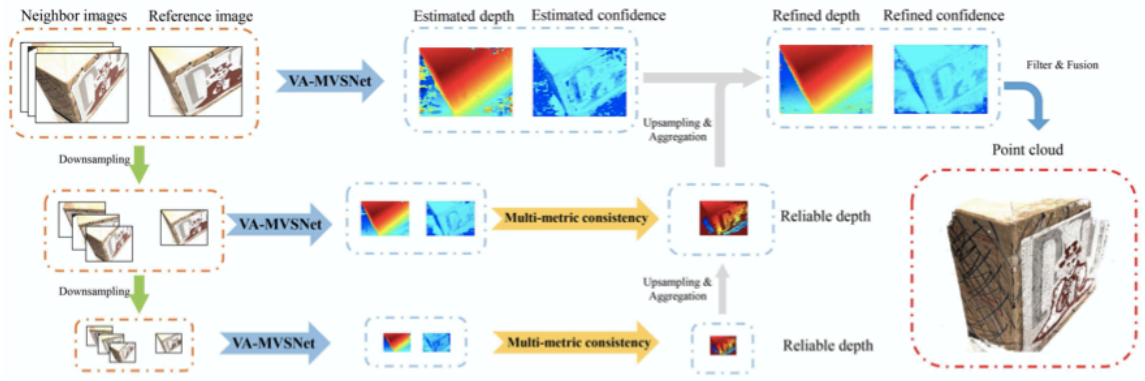
VA-MVSNet

Coarse to fine
多尺度特征图构建多cost volume联合估计



PVA-MVSNet

Coarse to fine
多尺度输入图分别经过VA-MVSNet结构
联合估计深度



特点 特征图金字塔和图片金字塔结构保证了重建的精度和准确度

缺点 相对MVSNet需要显存变大，用算力换精度

1.Yi, H., Wei, Z., Ding, M., Zhang, R., Chen, Y., Wang, G., & Tai, Y. (2019). Pyramid Multi-view Stereo Net with Self-adaptive View Aggregation. ArXiv, abs/1912.03001.
2. Yang, J., Mao, W., Alvarez, J.M., & Liu, M. (2019). Cost Volume Pyramid Based Depth Inference for Multi-View Stereo. ArXiv, abs/1912.08329.

Fast-MVSNet

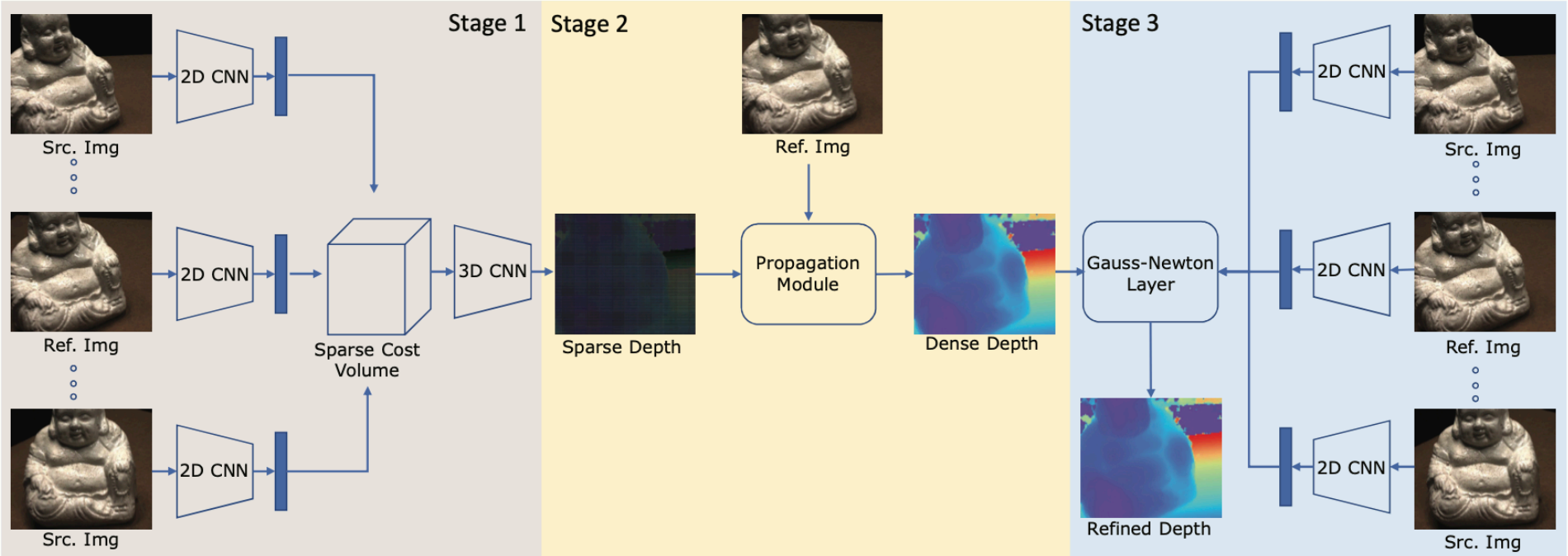


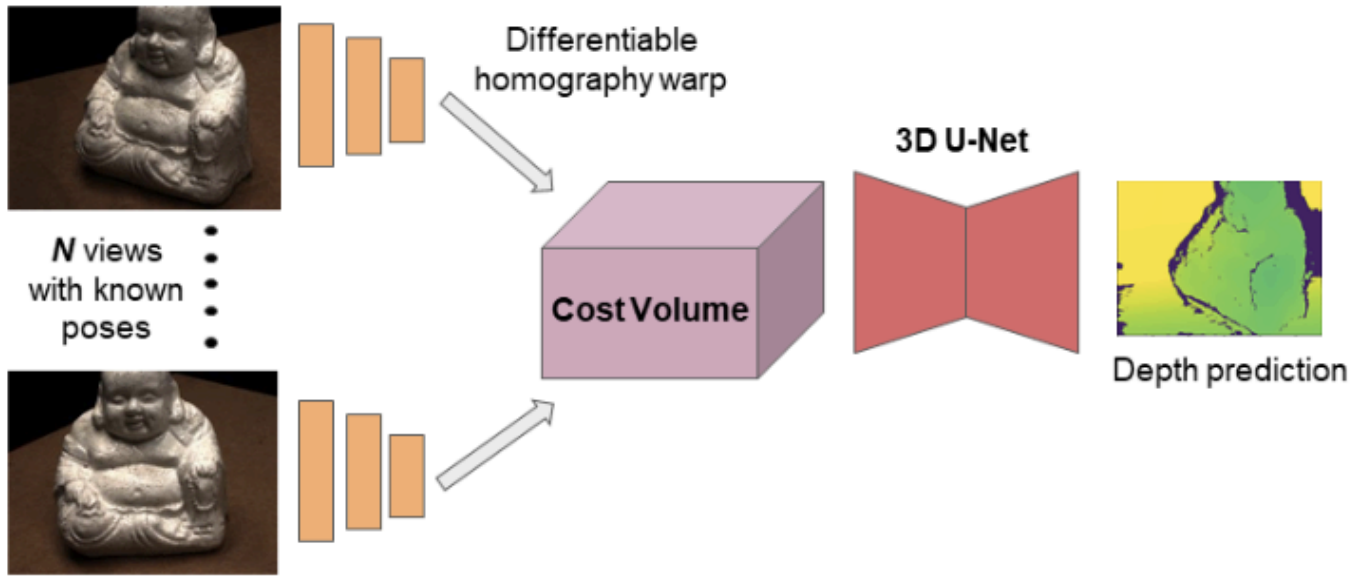
Figure 1: Network architecure of the Fast-MVSNet. In the **first stage**, we construct a sparse cost volume upon 2D CNN features and predict a sparse high-resolution depth map using a 3D CNN. In the **second stage**, we design a simple but efficient network to propagate the sparse depth map to a dense depth map. In the **third stage**, we propose a differentiable Gauss-Newton layer to further refine the depth map.

特点 先构造稀疏的cost volume去得到低分辨率的深度图，然后利用原图和gauss-newtow层去refine

Yu, Z., & Gao, S. (2020). Fast-mvsnet: Sparse-to-dense multi-view stereo with learned propagation and gauss-newton refinement. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 1949-1958).

Unsupervised MVSNet

自监督 利用投影光度一致性误差来产生自监督损失
自监督容易快速拓展到实际的生产应用中



Loss

$$Loss = \Sigma(\alpha L_{photo} + \beta L_{SSIM} + \gamma L_{smooth})$$

$$I'_r = I_s(KTD_rK^{-1}I_r)$$

$$L_{photo} = \sum_{m=1}^{M} ||(I_r - I'_r) \cdot V_r^m|| + ||(\nabla I_r - \nabla I'_r) \cdot V_r^m||$$

$$L_{SSIM} = \Sigma[1 - SSIM(I_r, I'_r)] \cdot V_r^m$$

$$L_{smooth} = \Sigma e^{-|\nabla I_r|} \cdot |\nabla D_r|$$

特点 利用估计的depth寻找匹配点和图像梯度的融合，克服了多视图下不重叠区域和遮挡，以及不同光照异性问题

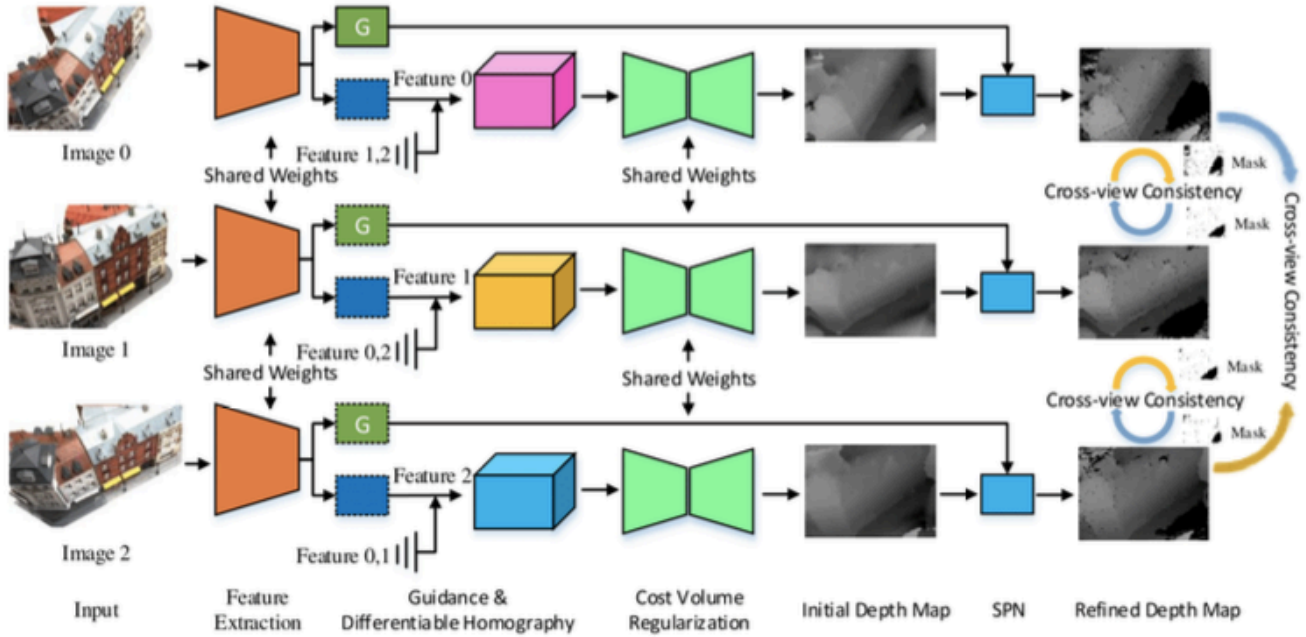
1.Khot, T., Agrawal, S., Tulsiani, S., Mertz, C., Lucey, S., & Hebert, M. (2019). Learning Unsupervised Multi-View Stereopsis via Robust Photometric Consistency. ArXiv, abs/1905.02706.

MVS^2

网络结构

从pixel-wise拓展到patch-wise cost volume

Hybrid 3D U-Net + depth修正高分辨率输出



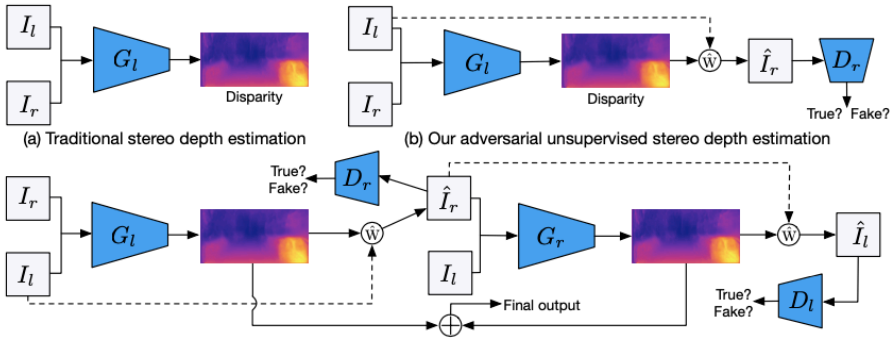
Loss

在之前Loss的基础上，加入了重投影光度误差，投影几何误差。

$$Loss \mathrel{+}= \Sigma \delta L_{reprojcted}$$

$$L_{reprojcted} = L(I_r, I_r'') + L(D_r, D_r') \cdot V_r$$

延伸-对抗网络自监督双目深度估计



特点 丰富了loss函数，效果更好，但是也更加耗费显存，MVS^2的显存耗费大约为上一个自监督网络的3倍

1.Dai, Y., Zhu, Z., Rao, Z., & Li, B. (2019). MVS2: Deep Unsupervised Multi-View Stereo with Multi-View Symmetry. 2019 International Conference on 3D Vision (3DV), 1-8.

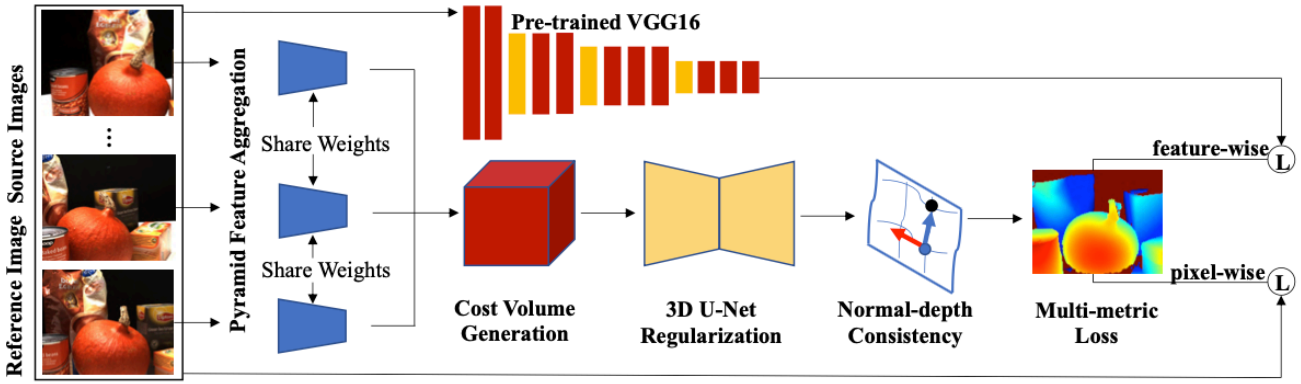
2.Pilzer, A., Xu, D.. (2018). Unsupervised Adversarial Depth Estimation Using Cycled Generative Networks. 2018 International Conference on 3D Vision (3DV), 587-595.

M^3VSNet

MEGVII 旷视

网络结构

把pixel-wise和feature-wise结合
在语义层次上做了初步的探索
结合法线的约束，进一步提高了深度精度



Result

无监督的效果直逼有监督

(a) Ground Truth (b) MVSNet (c) M^3VSNet w/o Feature-wise Loss (d) M^3VSNet

特点 无监督MVS领域一个相对轻量化的，结合语义信息的网络结构

Huang, Baichuan, et al. "M^ 3VSNet: Unsupervised Multi-metric Multi-view Stereo Network." arXiv preprint arXiv:2005.00363 (2020).

JDACS-MS

网络结构

3个branch：
1. 语义提取
2. 正常的深度图估计
3. 数据增强

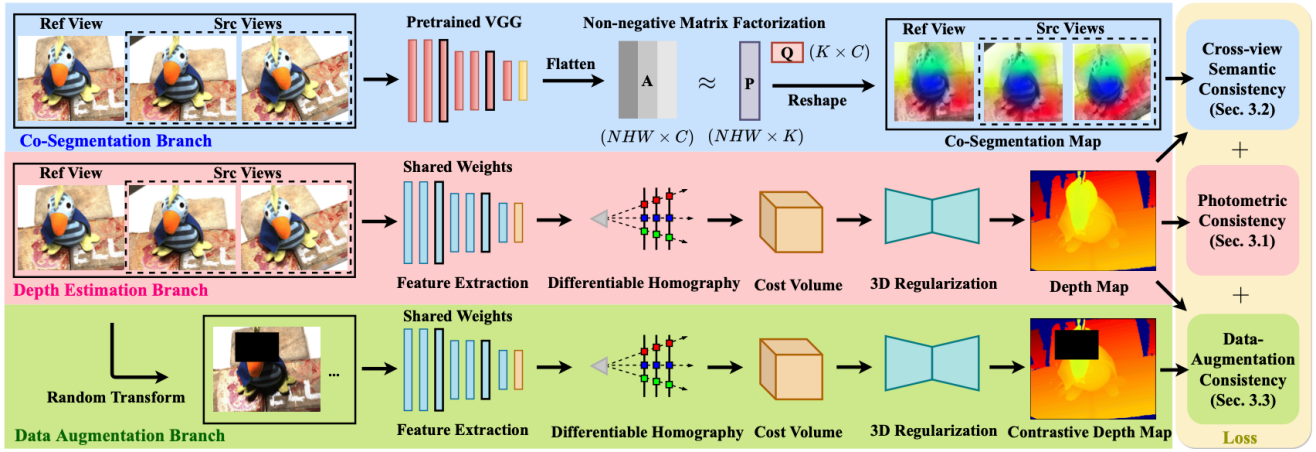


Figure 3: Illustration of our Joint Data-Augmentation and Co-Segmentation (JDACS) MVS framework.

Result

截止到2020.12.31，效果最好的无监督MVS网络

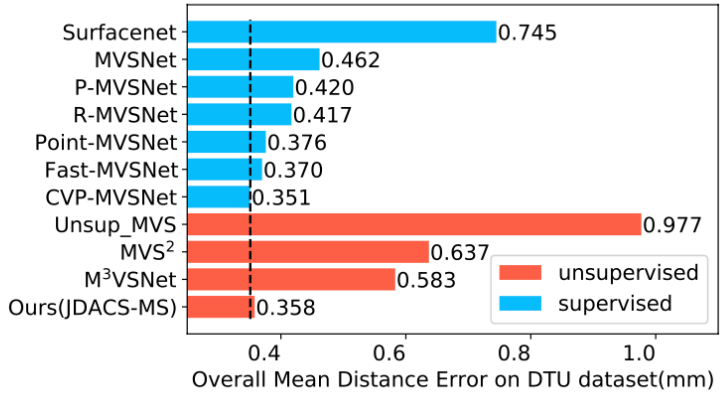


Figure 1: Comparison between SOTA supervised and unsupervised MVS methods.

特点 其实不管是语义提取还是数据增强，都是为了抵抗不同视角下color不完全一致的问题

谢谢观看！

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