Robot Vision:
Multi-view Stereo

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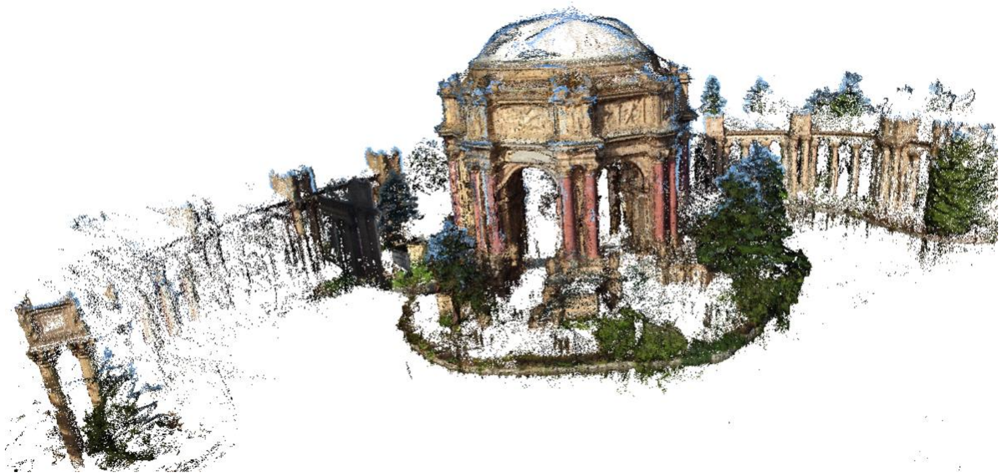
Outline

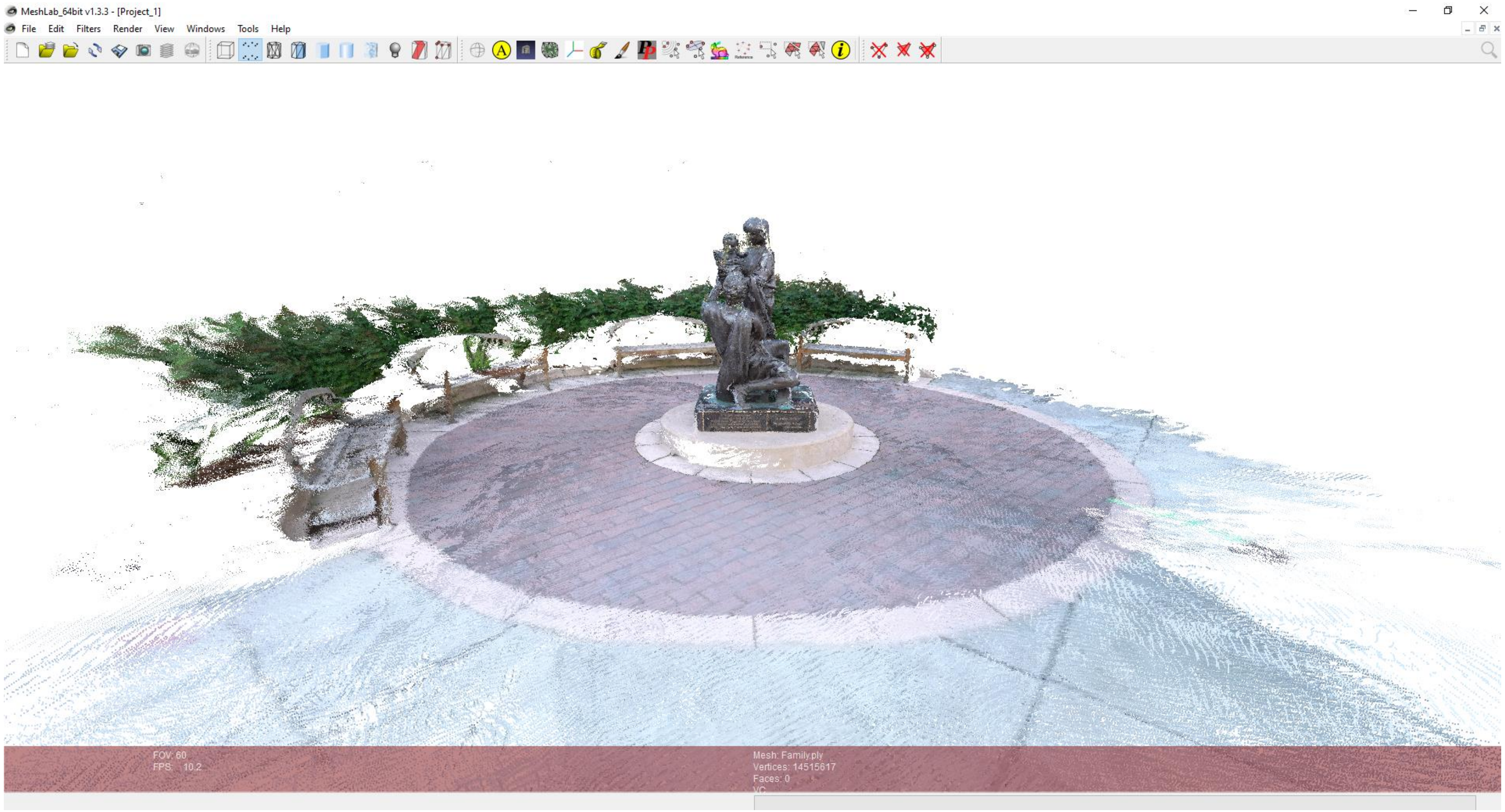
- Multi-view stereo principle
- Feature extraction networks
- Cost volume generation
- Cost volume regularization
- Depth inference
- Data sets
- Results

Multi-View Stereo

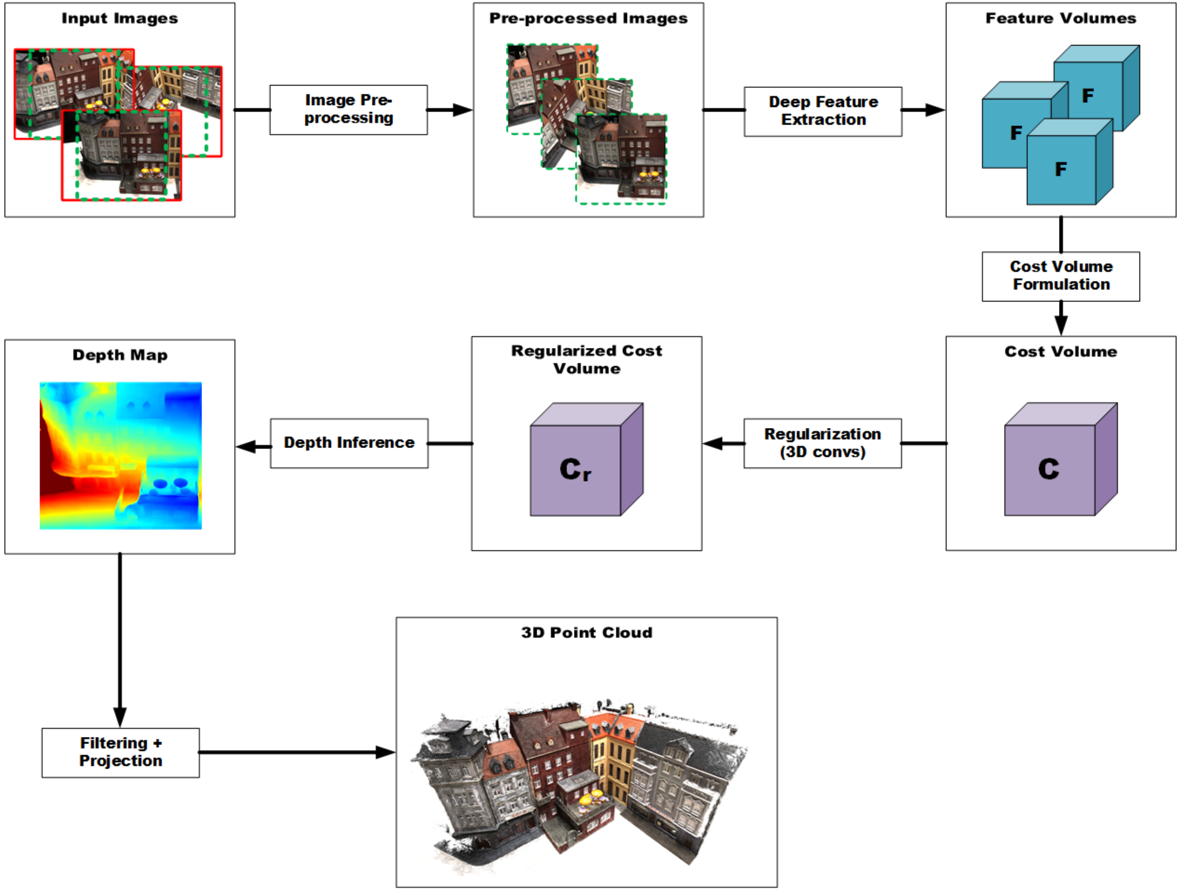
- Input: set of images + camera poses (from SFM)
- Output: 3D model (as dense point cloud)



Example

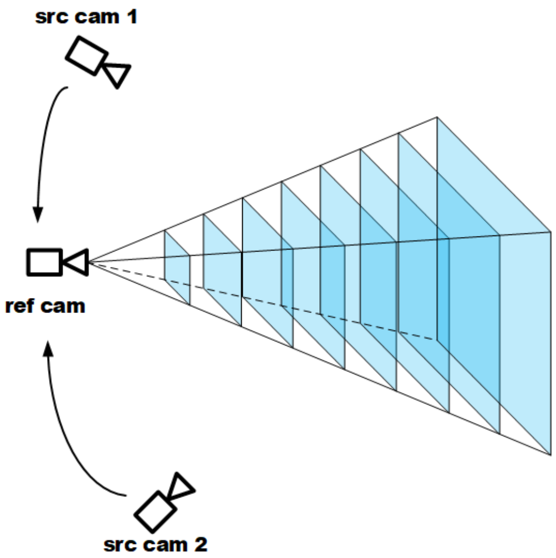

MeshLab_64bit v1.3.3 - [Project_1]
File Edit Filters Render View Windows Tools Help
FOV: 60
FPS: 10.2
Mesh: Family.ply
Vertices: 14515617
Faces: 0

Multi-View Stereo Pipeline



Plane-sweep multi-view stereo

- Classical plane sweeping stereo [8]
- Sweep family of planes at different depths with respect to reference camera
- With CNNs: Warp deep features instead of raw pixel values



$$H_i(d) = K_i \cdot R_i \cdot \left(I - \frac{(t_{ref} - t_i) \cdot n_{ref}^T}{d} \right) \cdot R_{ref}^T \cdot K_{ref}^T$$

Deep Learning for Multi-View Stereo (MVS)

- Advantages:
  - fast
  - usually works better in terms of completeness
  - can work on non-lambertian surfaces
- Disadvantages:
  - often huge (GPU) memory requirements
  - needs large amount of data to train on
  - might fail in a completely new environment

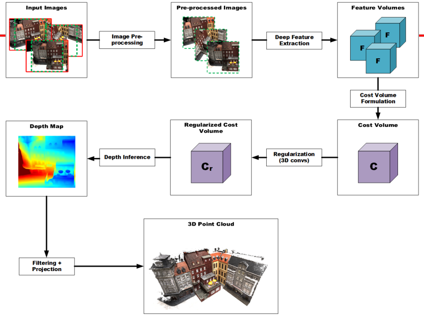
Deep Learning for MVS: Features

- Hand-crafted Features:
    - Designed by human experts to extract a given set of chosen characteristics
    - Trade-off between accuracy and computational efficiency
    - e.g.: Census
- Learned Features:
    - Extracted via Convolutional Neural Network (CNN)
    - Learned from data

Deep Learning for MVS: Regularization

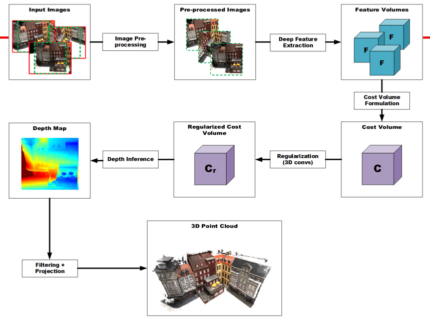
- Needed to filter incorrect correspondences (e.g. from occlusions, noise)
- Traditional Regularization:
  - Find local correspondences
  - Apply regularization methods
    - Semi global matching
    - Belief propagation
    - Graph cut
    - Smoothness priors
  - Apply filters
- Learned Regularization:
  - Network learns to regularize raw feature output
  - Often 3D convolutions

Pre-process Images



- Crop/scale to fit network requirements
  - Due to convolutions, width/height usually need to be a multiple of 2^n (e.g. 32 or 64)
  - Adjust camera parameters accordingly!
- Images usually need to be stacked in network -> need same sizes!
- Augment data for training: Change brightness, contrast, etc

Deep Feature Extraction



- Acquired from RGB image via CNN
- Encode image information in a way that it can be compared to other images
- Can have many layers
  - Usually a combination of 2D convolutions, Normalization and ReLU
- Original neighboring information can be encoded to smaller resolution
  - Save memory for next step

Deep Feature Extraction: 2D Convolution

- Example: Kernel=3x3, Stride = 1

$$\underbrace{\begin{pmatrix} 0 & 1_{\times 1} & 1_{\times 0} & 1_{\times 1} & 0 & 0 \\ 0 & 0_{\times 0} & 1_{\times 1} & 1_{\times 0} & 1 & 0 \\ 0 & 0_{\times 1} & 0_{\times 0} & 1_{\times 1} & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \end{pmatrix}}_{I} * \underbrace{\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}}_{K} = \underbrace{\begin{pmatrix} 1 & 4 & 3 & 4 \\ 1 & 2 & 4 & 3 \\ 1 & 2 & 3 & 4 \\ 1 & 3 & 3 & 1 \end{pmatrix}}_{I * K}$$

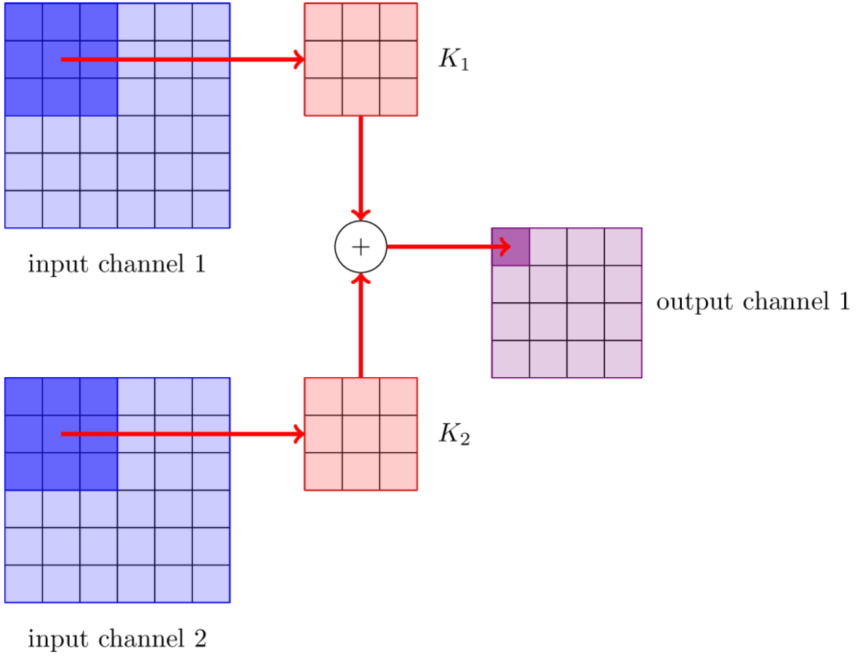
Deep Feature Extraction: 2D Convolution

- Example: Kernel=3x3, Stride = 3

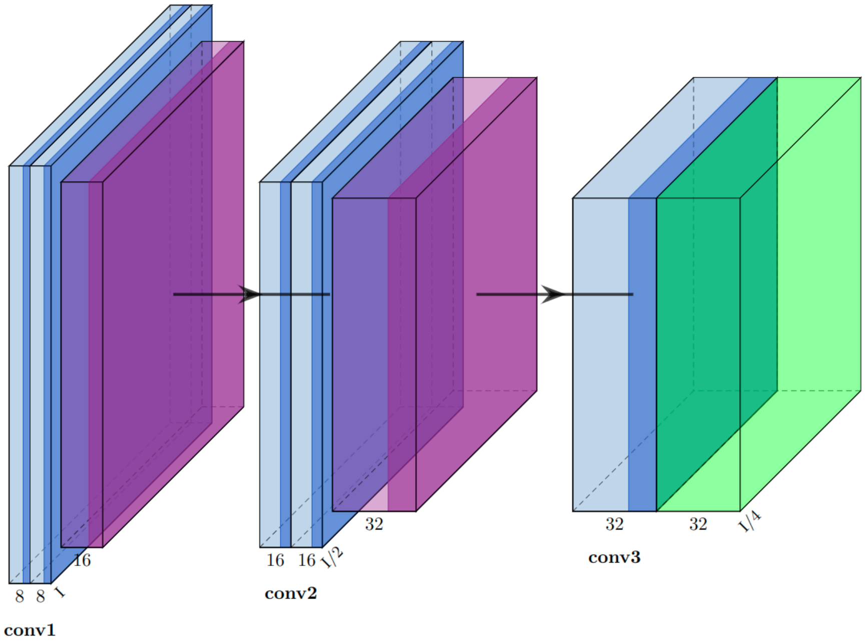
$$\underbrace{\begin{pmatrix} 0&1&1&1&0&0\\ 0&0&1&1&1&0\\ 0&0&0&1&1&1\\ 0&0&0&1&1&0\\ 0&0&1&1&0&0\\ 0&1&1&0&0&0 \end{pmatrix}}_{I} * \underbrace{\begin{pmatrix} 1&0&1\\ 0&1&0\\ 1&0&1 \end{pmatrix}}_{K} = \underbrace{\begin{pmatrix} 1&\boxed{4}\\ 1&1 \end{pmatrix}}_{I*K}$$

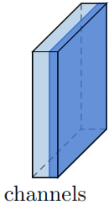
Deep Feature Extraction: 2D Convolution

- Input and output channels can be arbitrary (modelled through more kernel weights)

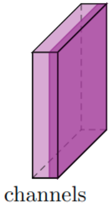


Ex. Deep Feature Extraction: Simple Feature Net

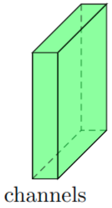




kernel=3x3, stride=1, BN, ReLU

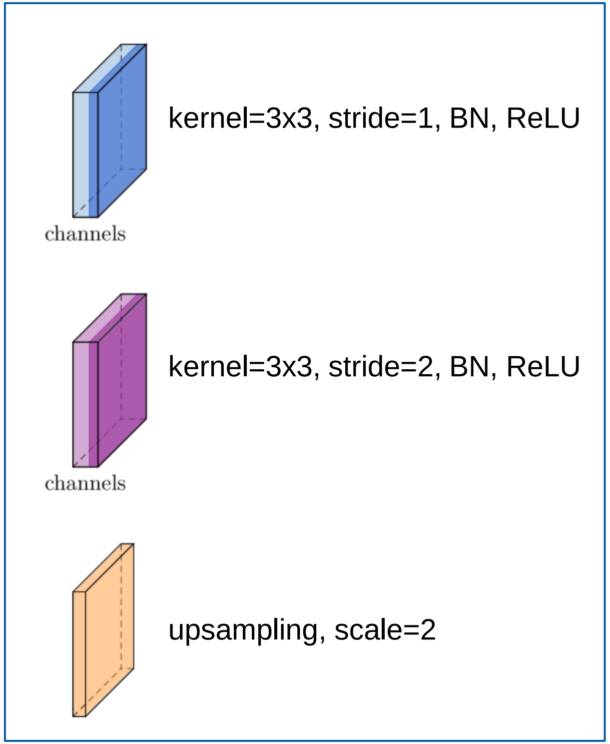


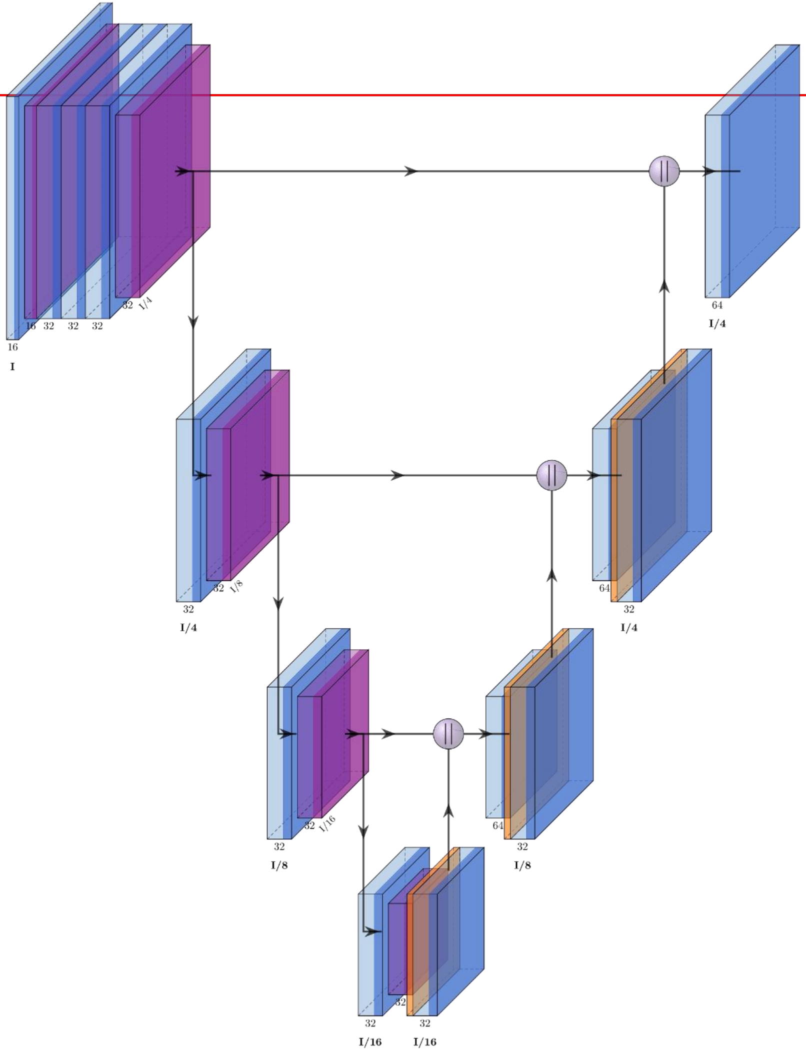
kernel=5x5, stride=2, BN, ReLU



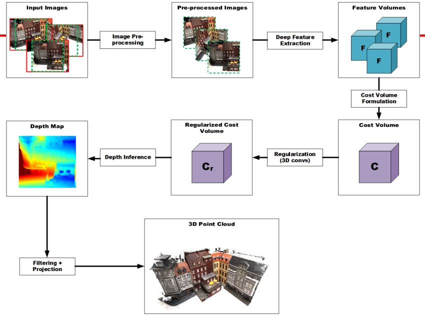
kernel=3x3, stride=1

Ex. Deep Feature Extraction: Unet





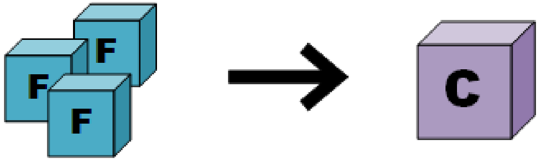
Cost Volume



- Aggregate N feature volumes to one cost volume C via
- homography warping (plane sweep)
- Variance cost metric using the average feature volume:

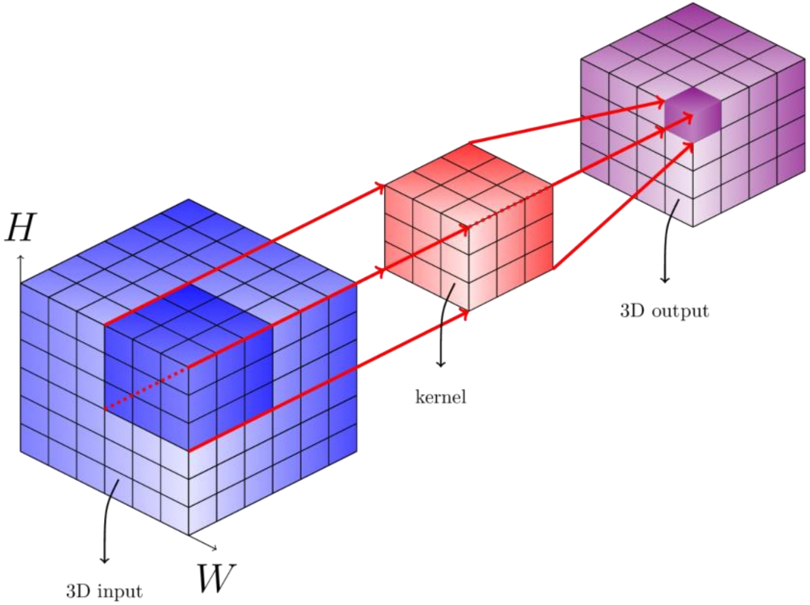
$$C = \frac{\sum_{i=1}^{N} (F_i - \bar{F}_i)^2}{N}$$

- Each point in the cost volume can be seen as a similarity measure



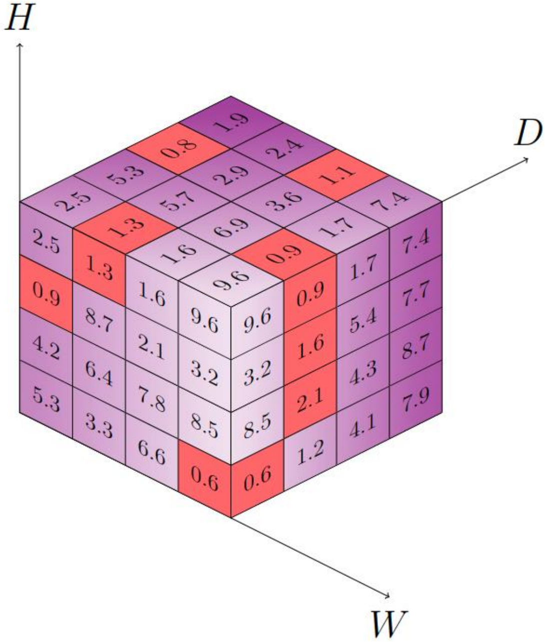
Cost Volume Regularization

- Raw cost volume
  - could be noise-contaminated
  - has no smoothness constraint
- Use CNNs to regularize the obtained cost volume variance
- Usually 3D convolutions



Cost Volume Regularization

- Last 3D convolution layer maps output to single channel
- Search for lowest cost / highest probability



Depth Inference

- Classification:
  - Predicts label
  - Discrete output: Class with highest probability
  - Can be filtered through probability threshold
  - Example: Class 4 has highest prob -> Result: 4
- Regression:
  - Predicts quantity
  - Continuous output
  - Can be filtered through entropy threshold
  - Example: 0.1*1 + 0.1*2 + 0.1*3 + 0.5*4 + 0.2*5 = 3.6

Network Output	Class Vector
0.1	1
0.1	2
0.1	3
0.5	4
0.2	5

Training loss: Classification

- Multi-class classification problem with cross entropy loss:

$$loss = \sum_{\mathbf{p}} \left(\sum_{i=1}^{D} -\mathbf{P}(i,\mathbf{p}) \cdot \log \mathbf{Q}(i,\mathbf{p}) \right)$$

where:

$$\begin{aligned}
\mathbf{p} &= \text{spatial image coordinate} \\
D &= \text{maximum depth value} \\
\mathbf{P}(i,\mathbf{p}) &= \text{voxel in the probability volume } \mathbf{P} \\
\mathbf{Q}(i,\mathbf{p}) &= \text{ground truth voxel}
\end{aligned}$$

Training loss: Regression

- Regress depth outputs using the soft argmin [7] operation and l1 loss:

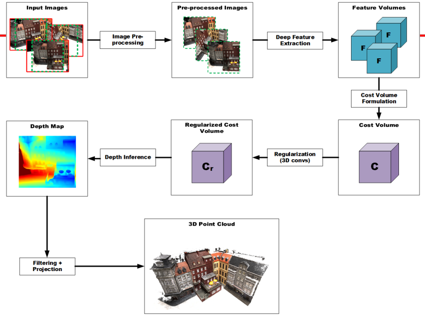
$$soft\ argmin := \sum_{d=1}^{D_{max}} d \times \sigma(-c_d)$$

where:

$$\begin{aligned} D_{max} &= \text{maximum depth value} \\ c_d &= \text{predicted cost} \\ \sigma(\cdot) &= \text{softmax operation} \end{aligned}$$

$$loss = \frac{1}{N} \sum_{n=1}^{N} \| d_{n,gt} - d_{n,pred} \|_1$$

Post-Processing and Filtering



- Geometric verification
  - Project each pixel into different view and back
  - Check if reprojected image lies within some threshold
- Photometric verification
  - Measures matching quality for each pixel
  - Directly implemented in network: probability, standard deviation or entropy

Datasets

- Quality of dataset very important for training
- Benchmarks for evaluation

- Examples: DTU, Tanks and Temples, ETH3D, Blended MVS

DTU dataset

- http://roboimagedata.compute.dtu.dk
- Recorded using industrial robot arm with a structured light scanner
- Indoor, small scale, different light settings, 49 or 64 images per scene
- Ground-truth available as point clouds
- “Ground-truth” depth maps available from MVSNet
  - Screened Poisson surface reconstruction: point cloud -> mesh
  - Render mesh to each viewpoint
  - Not perfect: holes and wrong labelling in depth maps
    - Attention-Aware MVS [6]: improve ground-truth depth maps

DTU dataset






Tanks and Temples dataset

- https://www.tanksandtemples.org/
- Ground-truth point cloud captured with industrial laser scanner
- Outdoor and indoor environments
- high-res video available for each scene

Tanks and Temples dataset

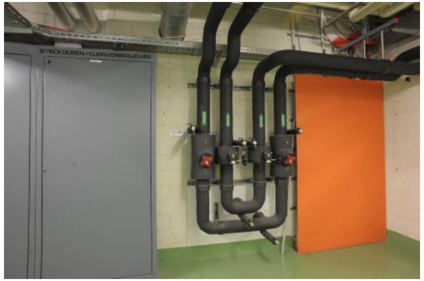




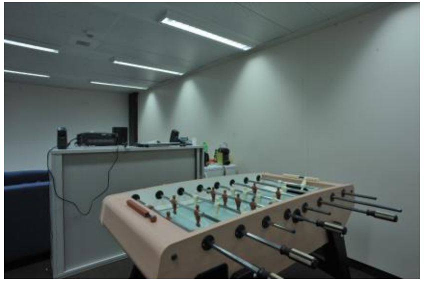
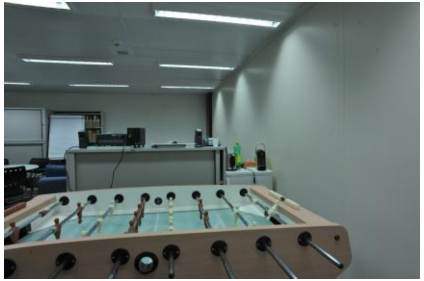

ETH3D dataset

- https://www.eth3d.net/datasets
- Ground-truth point cloud from laser scan
- 13 training and 12 test scenes in high resolution
- 5 training and 5 test videos in low resolution
- Challenging
  - large image size
  - large viewpoint change
  - small amount of images
- Deep learning methods not (yet) competitive

ETH3D dataset





Evaluation

- Overall Score: mean of accuracy and completeness (DTU)
  - Measures the mean distance to the groundtruth point cloud
  - Lower is better
- F-Score: harmonic mean of precision and recall (TaT, ETH3D)
  - Measured at a certain distance threshold d
  - If either $P(d) \rightarrow 0$ or $R(d) \rightarrow 0$, then $F(d) \rightarrow 0$
  - Better summary measure than the arithmetic mean

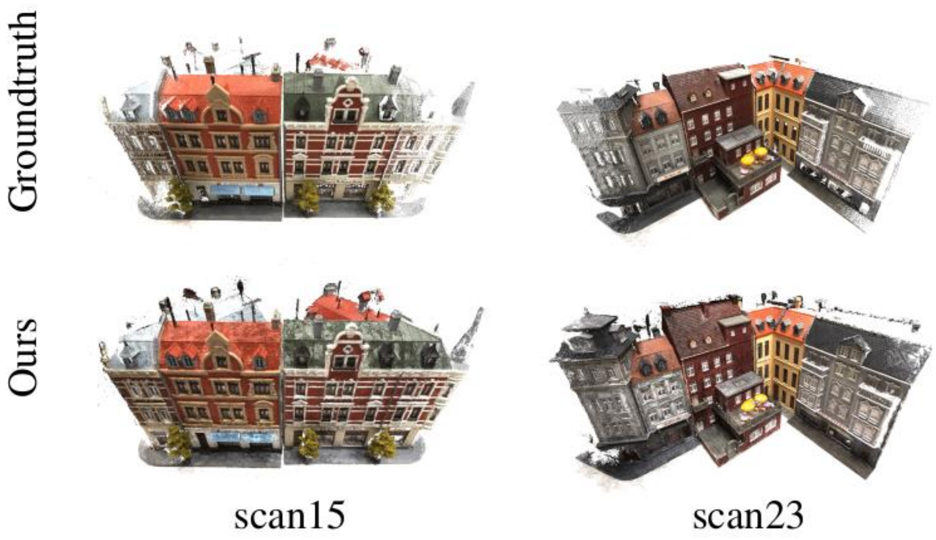
$$F(d) = \frac{2P(d)R(d)}{P(d) + R(d)}$$

Examples

- MVSNet (ECCV 2018): CostRegNet after volume variance calculation
- R-MVSNet (CVPR 2019): regularizes 2D costmaps along depth direction via GRU to save memory
- MVSCRF (ICCV 2019): CRF after cost volume regularization
- CasMVSNet (CVPR 2020): Multiscale feature extraction, refine depth values in every step
- Cost Volume Pyramid (CVPR 2020)
- Attention-Aware MVS (CVPR 2020)

HighRes-MVSNet: Evaluation DTU

	Method	Acc.	Comp.	Overall
Geometric	Furu [6]	0.613	0.941	0.777
	Tola [27]	0.342	1.190	0.766
	Camp [2]	0.835	0.554	0.695
	Gipuma [7]	**0.283**	0.873	0.578
	COLMAP [25, 26]	0.400	0.664	0.532
Learning	MVSNet [32]	0.396	0.527	0.462
	R-MVSNet [33]	0.383	0.452	0.417
	SurfaceNet [14]	0.450	1.040	0.745
	MVSCRF [29]	0.371	0.426	0.398
	Point-MVSNet [4]	0.342	0.411	0.376
	CasMVSNet [9]	0.346	0.351	0.348
	CVP-MVSNet [31]	0.296	0.406	0.351
	AttMVS [20]	0.383	**0.329**	0.356
	Fast-MVSNet [35]	0.336	0.403	0.370
	Ours	0.354	0.393	0.373
	Ours(HR)	0.346	0.345	**0.346**



HighRes-MVSNet: Evaluation TaT

Method	Mean	Family	Francis	Horse	Lighthouse	M60	Panther	Playground	Train
COLMAP [25, 26]	42.41	50.41	22.25	25.63	56.43	44.83	46.97	48.53	42.04
MVSNet [32]	43.48	55.99	28.55	25.07	50.79	53.96	50.86	47.90	34.69
R-MVSNet [33]	48.40	69.96	46.65	32.59	42.95	51.88	48.80	52.00	42.38
Point-MVSNet [4]	48.27	61.79	41.15	34.20	50.79	51.97	50.85	52.38	43.06
AttMVS [20]	60.05	73.90	62.58	44.08	64.88	56.08	59.39	63.42	56.06
CasMVSNet [9]	56.42	76.36	58.45	46.20	55.53	56.11	54.02	58.17	46.56
CVP-MVSNet [31]	54.03	76.50	47.74	36.34	55.12	57.28	54.28	57.43	47.54
MVSCRF [29]	45.73	59.83	30.60	29.93	51.15	50.61	51.45	52.60	39.68
Fast-MVSNet [35]	47.39	65.18	39.59	34.98	47.81	49.16	46.20	53.27	42.91
Ours	49.81	66.62	44.17	30.84	55.13	53.20	50.32	55.45	42.73

References

[1] [MVSNet] Yao, Y., Luo, Z., Li, S., Fang, T., & Quan, L. (2018). Mvsnet: Depth inference for unstructured multi-view stereo. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 767-783).

[2] [R-MVSNet] Yao, Y., Luo, Z., Li, S., Shen, T., Fang, T., & Quan, L. (2019). Recurrent mvsnet for high-resolution multi-view stereo depth inference. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5525-5534).

[3] [MVSCRF] Xue, Y., Chen, J., Wan, W., Huang, Y., Yu, C., Li, T., & Bao, J. (2019). Mvscrf: Learning multi-view stereo with conditional random fields. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 4312-4321).

[4] [CasMVSNet] Gu, X., Fan, Z., Zhu, S., Dai, Z., Tan, F., & Tan, P. (2020). 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* (pp. 2495-2504).

[5] [Cost Volume Pyramid] Yang, J., Mao, W., Alvarez, J. M., & Liu, M. (2020). Cost Volume Pyramid Based Depth Inference for Multi-View Stereo. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 4877-4886).

[6] [Attention MVS] Luo, K., Guan, T., Ju, L., Wang, Y., Chen, Z., & Luo, Y. (2020). Attention-Aware Multi-View Stereo. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 1590-1599).

References

[7] Kendall, A., Martirosyan, H., Dasgupta, S., Henry, P., Kennedy, R., Bachrach, A., & Bry, A. (2017). End-to-end learning of geometry and context for deep stereo regression. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 66-75).

[8] Collins, R. T. (1996, June). A space-sweep approach to true multi-image matching. In *Proceedings CVPR IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (pp. 358-363).

References

[DTU] Aanæs, H., Jensen, R. R., Vogiatzis, G., Tola, E., & Dahl, A. B. (2016). Large-scale data for multiple-view stereopsis. *International Journal of Computer Vision*, *120*(2), 153-168.

[Blended MVS] Yao, Y., Luo, Z., Li, S., Zhang, J., Ren, Y., Zhou, L., ... & Quan, L. (2020). BlendedMVS: A Large-scale Dataset for Generalized Multi-view Stereo Networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 1790-1799).

[ETH3D] Schöps, T., Schönberger, J. L., Galliani, S., Sattler, T., Schindler, K., Pollefeys, M., & Geiger, A. (2018). Eth3d benchmark.

[Tanks and Temples] Knapitsch, A., Park, J., Zhou, Q. Y., & Koltun, V. (2017). Tanks and temples: Benchmarking large-scale scene reconstruction. *ACM Transactions on Graphics (ToG)*, *36*(4), 1-13.