Cascade Cost Volume for High-Resolution Multi-View Stereo and Stereo Matching

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Abstract

The deep multi-view stereo (MVS) and stereo matching approaches generally construct 3D cost volumes to regularize and regress the depth or disparity. These methods are limited with high-resolution outputs since the memory and time costs grow cubically as the volume resolution increases. In this paper, we propose a memory and time efficient cost volume formulation complementary to existing multi-view stereo and stereo matching approaches based on 3D cost volumes. First, the proposed cost volume is built upon a feature pyramid encoding geometry and context at gradually finer scales. Then, we can narrow the depth (or disparity) range of each stage by the prediction from the previous stage. With gradually higher cost volume resolution and adaptive adjustment of depth (or disparity) intervals, the output is recovered in a coarser to fine manner.

We apply the cascade cost volume to the representative MVS-Net, and obtain a 23.1% improvement on DTU benchmark (1st place), with 50.6% and 59.3% reduction in GPU memory and run-time. It is also rank first on Tanks and Temples benchmark of all deep models. The statistics of accuracy, run-time and GPU memory on other representative stereo CNNs also validate the effectiveness of our proposed method. Our source code are available at https://github.com/alibaba/cascade-stereo.

1. Introduction

Convolutional neural networks (CNNs) have been widely adopted in 3D reconstruction and broader computer vision tasks. State-of-the-art multi-view stereo [12, 22, 44, 45] and stereo matching algorithms [3, 8, 15, 26, 38, 48] often compute a 3D cost volume according to a set of hypothesized depth (or disparity) and warped features. 3D convolutions are applied to this cost volume to regularize and regress the final scene depth (or disparity).

Compared with the methods based on 2D CNNs [23, 47], the 3D cost volume can capture better geometry structures, perform photometric matching in 3D space, and alleviate the influence of image distortion caused by perspective transformation and occlusions [4]. However, methods relying on 3D cost volumes are often limited to low-resolution input images (and results), because 3D CNNs are generally time and GPU memory consuming. Typically, these methods downsample the feature maps to formulate the cost volumes at a lower resolution [3, 4, 8, 12, 15, 22, 26, 34, 38, 41, 48] and adopt upsampling [3, 8, 15, 26, 34, 38, 41, 48] or post-refinement [4, 22] to output the final high-resolution result.

In this work, we present a novel cascade formulation of 3D cost volumes. We start from a feature pyramid to extract multi-scale features which are commonly used in standard multi-view stereo [44] and stereo matching [3, 8] networks. In a coarse-to-fine manner, the cost volume at
the early stages is built upon larger scale semantic 2D features with sparsely sampled depth hypotheses, which lead to a relatively lower volume resolution. Subsequently, the later stages use the estimated depth (or disparity) maps from the earlier stages to adaptively adjust the sampling range of depth (or disparity) hypotheses and construct new cost volumes where finer semantic features are applied. This adaptive depth sampling and adjustment of feature resolution ensures the computation and memory resources are spent on more meaningful regions. In this way, our cascade structure can remarkably decrease computation time and GPU memory consumption. The effectiveness of our method can be seen in Figure 1.

We validate our method on both multi-view stereo and stereo matching on various benchmark datasets. For multi-view stereo, our cascade structure achieves the best performance on the DTU dataset [1] at the submission time of this paper, when combined with MVSNet [44]. It is also the state-of-the-art learning-based method on Tanks and Temples benchmark [17]. For stereo matching, our method reduces the end-point-error (EPE) and GPU memory consumption of GwcNet [8] by about 15.2% and 36.9% respectively.

2. Related Work

Stereo Matching According to the survey by Scharstein et al. [30], a typical stereo matching algorithm contains four steps: matching cost calculation, matching cost aggregation, disparity calculation, and disparity refinement. Local methods [24, 42, 49] aggregate matching costs with neighboring pixels and usually utilize the winner-take-all strategy to choose the optimal disparity. Global methods [10, 16, 35] construct an energy function and try to minimize it to find the optimal disparity. More specifically, works in [16, 35] use belief propagation and semi-global matching [10] to approximate the global optimization with dynamic programming.

In the context of deep neural networks, CNNs based stereo matching methods are first introduced by Zhontar and LeCun [46], in which a convolutional neural network is introduced to learn the similarity measure of small patch pairs. The introduction of the widely used 3D cost volume in stereo is first proposed in GCNet [15], in which the disparity regression step uses the soft argmin operation to figure out the best matching results. PSMNet [3] further introduces pyramid spatial pooling and 3D hourglass networks for cost volume regularization and yields better results. GwcNet [8] modifies the structure of 3D hourglass and introduces group wise correlation to form a group based 3D cost volume. HSM [40] builds a light model for high-resolution images with a hierarchical design. EMCUA [26] introduces an approach for multi-level context ultra-aggregation. GANet [48] constructs several semi-global aggregation layers and local guided aggregation layers to further improve the accuracy.

Although methods based on 3D cost-volume remarkably boost the performance, they are limited to downsampled cost volumes and rely on interpolation operations to generate high-resolution disparity. Our cascade cost volumes can be combined with these methods to improve the disparity accuracy and GPU memory efficiency.

Multi-View Stereo According to the comprehensive survey [5], works in traditional multi-view stereo can be roughly categorized into volumetric methods [13, 14, 18, 33], which estimate the relationship between each voxel and surfaces; point cloud based methods [6, 19], which directly process 3D points to iteratively densify the results; and depth map reconstruction methods [2, 7, 32, 36, 43], which use only one reference and a few source images for single depth map estimation.

Recently, learning-based approaches also demonstrate superior performance on multi-view stereo. Multi-patch similarity [9] introduces a learned cost metric. SurfaceNet [13] and DeepMVS [11] pre-warp the multi-view images to 3D space and use deep networks for regularization and aggregation. Most recently, multi-view stereo based on 3D cost volumes have been proposed in [4, 12, 22, 44, 45]. A 3D cost volume is built based on warped 2D image features from multiple views and 3D CNNs are applied for cost regularization and depth regression. Because the 3D CNNs require large GPU memory, these methods generally use downsampled cost volumes. Our cascade cost volume can be easily integrated into these methods to enable high-resolution cost volumes and further boosts accuracy, computational speed, and GPU memory efficiency.

High-Resolution Output in Stereo and MVS Recently, some learning-based methods try to reduce the memory requirement in order to generate high-resolution outputs. Instead of using voxel grids, Point MVSNet [4] proposes to use a small cost volume to generate the coarse depth and uses a point-based iterative refinement network to output the full resolution depth. In comparison, a standard MVSNet combined with our cascade cost volume can output full resolution depth with superior accuracy using less runtime and GPU memory than Point MVSNet [4]. Works in [28, 28, 37] partition advanced space to reduce memory consumption and construct a fixed cost volume representation which lacks flexibility. Works in [22, 34, 41] build extra refinement module by 2D CNNs and output a high resolution prediction. Notably, such refinement modules can be utilized jointly with our proposed cascade cost volume.

3. Methodology

This section describes the detailed architecture of the proposed cascade cost volume which is complementary to
the existing 3D cost volume based methods in multi-view stereo and stereo matching. Here, we use the representative MVSNet [44] and PSMNet [3] as the backbone networks to demonstrate the application of the cascade cost volume in multi-view stereo and stereo matching tasks respectively. Figure 2 shows the architecture of MVSNet+Ours.

3.1. Cost Volume Formulation

Learning-based multi-view stereo [4, 44, 45] and stereo matching [3, 8, 15, 46, 48] construct 3D cost volumes to measure the similarity between corresponding image patches and determine whether they are matched. Constructing 3D cost volume requires three major steps in both multi-view stereo and stereo matching. First, the discrete hypothesis depth (or disparity) planes are determined. Then, we warp the extracted 2D features of each view to the hypothesis planes and construct the feature volumes, which are finally fused together to build the 3D cost volume. Pixel-wise cost calculation is generally ambiguous in inherently ill-posed regions such as occlusion areas, repeated patterns, textureless regions, and reflective surfaces. To solve this, 3D CNNs at multiple scales are generally introduced to aggregate contextual information and regularize the possibly noise-contaminated cost volumes.

3D Cost Volumes in Multi-View Stereo

MVSNet [44] proposes to use front-to-parallel planes at different depth as hypothesis planes and the depth range is generally determined by the sparse reconstruction. The coordinate mapping is determined by the homography:

$$H_i(d) = K_i \cdot R_i \cdot (I - (t_1 - t_i) \cdot n_1^T / d) \cdot R_1^T \cdot K_1^{-1}$$

where $H_i(d)$ refers to the homography between the feature maps of the $i^{th}$ view and the reference feature maps at depth $d$. Moreover, $K_i, R_i, t_i$ refers to the camera intrinsics, rotations and translations of the $i^{th}$ view respectively, and $n_1$ denotes the principle axis of the reference camera. Then differentiable homography is used to warp 2D feature maps into hypothesis planes of the reference camera to form feature volumes. To aggregate multiple feature volumes to one cost volume, the variance-based cost metric is proposed to adapt an arbitrary number of input feature volumes.

3D Cost Volumes in Stereo Matching

PSMNet [3] uses disparity levels as hypothesis planes and the range of disparity is designed according to specific scenes. Since the left and right images have been rectified, the coordinate mapping is determined by the offset in the x-axis direction:

$$C_r(d) = X_l - d$$

where $C_r(d)$ refers to the transformed x-axis coordinate of the right view at disparity $d$, and $X_l$ is the source x-axis coordinate of the left view. To build feature volumes, we warp the feature maps of the right view to the left view using the translation along the x-axis. There are multiple ways to build the final cost volume. GCNet [15] and PSMNet [3] concatenate the left feature volume and the right feature volume without decreasing the feature dimension. The work [47] uses the sum of absolute differences to compute matching cost. DispNetC [23] computes full correlation about the left feature volume and right feature volume without decreasing the feature dimension. The work [47] uses the sum of absolute differences to compute matching cost. GwcNet [8] proposes group-wise correlation by splitting the features into groups and computing correlation maps in each group.
Based on the cascade formulation, we can effectively reduce results while leads to increased GPU memory and run-time.

more hypothesis planes and correspondingly more accurate resolution of a cost volume is fixed, a larger \( D \) the corresponding number of hypothesis planes.

definition in \([4,44,45]\), an increased number of plane hypothesis \( D \), a larger spatial resolution \( W \times H \), and a finer plane interval are likely to improve the reconstruction accuracy. However, the GPU memory and run-time grow cubically as the resolution of the cost volume increases. As demonstrated in R-MVSNet \([45]\), MVSNet \([44]\) is able to process a maximum solution of the cost volume increases.

Following the practices of Feature Pyramid Network \([21]\), we double the spatial resolution of the cost volume at every stage along with the doubled resolution of the input feature maps. We define \( N \) as the total stage number of cascade cost volume, then the spatial resolution of cost volume at the \( k^{th} \) stage is defined as \( \frac{W}{2^N} \times \frac{H}{2^N} \). We set \( N = 3 \) in multi-view stereo tasks and \( N = 2 \) in stereo matching tasks.

Applying the cascade cost volume formulation to multi-view stereo, we base on Equation 1 and rewrite the homography warping function at the \((k+1)^{th}\) stage as:

\[
H_i(d_{k}^m + \Delta_{k+1}^m) = K_i \cdot R_i \cdot (I - \frac{(t_1 - t_i) \cdot n_1^T}{d_{k}^m + \Delta_{k+1}^m}) \cdot R_1^T \cdot K_1^{-1}
\]

where \( d_{k}^m \) denotes the predicted depth of the \( m^{th} \) pixel at the \( k^{th} \) stage, and \( \Delta_{k+1}^m \) is the residual depth of the \( m^{th} \) pixel to be learned at the \( k + 1^{st} \) stage.

Similarly in stereo matching, we reformulate Equation 2 based on our cascade cost volume. The \( m^{th} \) pixel coordinate mapping at the \( k + 1 \) stage is expressed as:

\[
C_r(d_{k}^m + \Delta_{k+1}^m) = X_i - (d_{k}^m + \Delta_{k+1}^m)
\]

where \( d_{k}^m \) denotes the predicted disparity of the \( m^{th} \) pixel at the \( k^{th} \) stage, and \( \Delta_{k+1}^m \) denotes the residual disparity of the \( m^{th} \) pixel to be learned at the \( k + 1^{st} \) stage.

At the \( k^{th} \) stage, given the hypothesis range \( R_k \) and hypothesis plane interval \( I_k \), the corresponding number of hypothesis planes \( D_k \) is determined by the equation: \( D_k = R_k / I_k \). When the spatial resolution of a cost volume is fixed, a larger \( D_k \) generates more hypothesis planes and correspondingly more accurate results while leads to increased GPU memory and run-time. Based on the cascade formulation, we can effectively reduce the total number of hypothesis planes since the hypothesis range is remarkably reduced stage by stage while still covering the entire output range.

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\]

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Figure 5: Multi-view stereo qualitative results of scan 10 on DTU dataset [1]. Top row: Generated point clouds of different methods and ground truth point clouds. Bottom row: Zoomed local areas.

| Methods               | Mean Acc. (mm) | Mean Comp. (mm) | Overall (mm) |
|-----------------------|----------------|-----------------|--------------|
| Camp [2]              | 0.835          | 0.554           | 0.695        |
| Furu [6]              | 0.613          | 0.941           | 0.777        |
| Tola [36]             | 0.342          | 1.190           | 0.766        |
| Gipuma [7]            | 0.283          | 0.873           | 0.578        |
| SurfaceNet [13]       | 0.450          | 1.040           | 0.745        |
| R-MVSNet(D=256) [45]  | 0.385          | 0.459           | 0.422        |
| R-MVSNet(D=512) [45]  | 0.383          | 0.452           | 0.417        |
| P-MVSNet [22]         | 0.406          | 0.434           | 0.420        |
| Point-MVSNet [4]      | 0.342          | 0.413           | 0.376        |
| MVSNet(D=192) [44]    | 0.456          | 0.646           | 0.551        |
| MVSNet(D=256) [44]    | 0.396          | 0.527           | 0.462        |
| MVSNet+Ours           | 0.325          | 0.383           | 0.355        |
| MVSNet+Ours(Hi-Res)   | 0.346          | 0.351           | 0.348        |

Table 2: Multi-view stereo quantitative results of different methods on DTU dataset [1] (lower is better). We conduct this experiment using two resolution settings according to PointMVSNet [4] where MVSNet+Ours uses resolution of 1152 × 864 and MVSNet+Ours(Hi-Res) uses 1600 × 1184 for testing.

and adopt its feature maps with increased spatial resolutions to build the cost volumes of higher resolutions. For example, when applying cascade cost volume to MVSNet [44], we build three cost volumes from the feature maps \{P1, P2, P3\} of Feature Pyramid Network [21]. Their corresponding spatial resolutions are \{1/16, 1/4, 1\} of the input image size.

3.4. Loss Function

The cascade cost volume with \(N\) stages produces \(N - 1\) intermediate outputs and a final prediction. We apply the supervision to all the outputs and the total loss is defined as:

\[
    \text{Loss} = \sum_{k=1}^{N} \lambda_k \cdot L_k
\]

where \(L_k\) refers to the loss at the \(k^{th}\) stage and \(\lambda_k\) refers to its corresponding loss weight. We adopt the same loss function \(L_k\) as the baseline networks in our experiments.

4. Experiments

We evaluate the proposed cascade cost volume on multi-view stereo and stereo matching tasks.

4.1. Multi-view stereo

Datasets DTU [1] is a large-scale MVS dataset consisting of 124 different scenes scanned in 7 different lighting conditions at 49 or 64 positions. Tanks and Temples dataset [17] contains realistic scenes with small depth ranges. More specifically, its intermediate set is consisted of 8 scenes including Family, Francis, Horse, Lighthouse, M60, Panther, Playground, and Train. Following the work [45], we use DTU training set [1] to train our method, and test on DTU evaluation set. To validate the generalization of our approach, we also test it on the intermediate set of Tanks and Temples dataset [17] using the model trained on DTU dataset without fine-tuning.
Figure 6: Point cloud results of MVSNet+Ours on the intermediate set of Tanks and Temples dataset [17].

Table 3: The statistical results of different stages in cascade cost volume. The statistics are collected on the DTU evaluation set [1] using MVSNet+Ours. The run-time is the sum of the current and previous stages. The base of resolution of input images in this experiment is 1152 $\times$ 864.

Table 4: Quantitative results of different stereo matching methods with and without cascade cost volume on Scene Flow dataset [23]. Accuracy, GPU memory consumption and run-time are included for comparisons.

Implementation We apply the proposed cascade cost volume to the representative MVSNet [44] and denote the network as MVSNet+Ours. During training, we set the number of input images to $N=3$ and image resolution to 640 $\times$ 512. After balancing accuracy and efficiency, we adopt a three-stage cascade cost volume. From the first to the third stage, the number of depth hypothesis is 48, 32 and 8, and the corresponding depth interval is set to 4, 2 and 1 times as the interval of MVSNet [44] respectively. Accordingly, the spatial resolution of feature maps gradually increases and is set to 1/16, 1/4 and 1 of the original input image size. We follow the same input view selection and data pre-processing strategies as MVSNet [44] in both training and evaluation. During training, we use Adam optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. The learning rate is set to 0.001 for 10 epochs, and downgraded by 2 after epoch 10, 12, and 14. The batch size is fixed to 16, and we train our method with 8 Nvidia GTX 1080Ti GPUs with 2 training samples on each GPU.

For quantitative evaluation on DTU dataset [1], we calculate the accuracy and the completeness by the MATLAB code provided by DTU dataset [1]. The percentage evaluation is implemented following MVSNet [44]. The F-score is used as the evaluation metric for Tanks and Temples dataset [17] to measure the accuracy and completeness of the reconstructed point clouds. We use fusible [29] as our post-processing consisting of three steps: photometric filtering, geometric consistency filtering, and depth fusion.

Benchmark Performance Quantitative results on DTU evaluation set [1] are shown in Table 2. We can see that MVSNet [44] with cascade cost volume outperforms other methods [4, 22, 44, 45] in both completeness and overall quality and rank the 1st place on DTU dataset [1]. The qualitative results are shown in Figure 5. We can see that MVSNet+Ours generates more complete point clouds with finer details. Besides, we demonstrate the generalization ability of our trained model by testing on Tanks and Temples dataset [17]. The corresponding quantitative results are reported in Table 1, and MVSNet+Ours achieves the state-of-the-art performance among the learning-based multi-view stereo methods. The qualitative point cloud results of the intermediate set of Tanks and Temples benchmark [17] are visualized in Figure 6. Note that, we get the results of above mentioned methods by running their provided pre-trained model and code except R-MVSNet [45] which provides point cloud results with their post-processing method.

To analyse the accuracy, GPU memory and run-time at each stage, we evaluate the MVSNet+Ours method on the DTU dataset [1]. We provide comprehensive statistics in Table 10 and visualization results in Figure 8. In a coarse-to-fine manner, the overall quality is improved from 0.602 to 0.355. Accordingly, the GPU memory increases from...
Table 5: Comparisons of MVSNet [44] with different cascade cost volume formulations.

| Methods         | All (%): 2mm | All (%): 4mm | All (%): 8mm | Acc. (mm): 2mm | Comp. (mm): 2mm | Overall (mm): 2mm | GPU Mem. (MB): 2mm | Run-time (s): 2mm |
|-----------------|--------------|--------------|--------------|---------------|----------------|--------------------|--------------------|------------------|
| MVSNet          | 0.271        | 0.173        | 0.124        | 0.456         | 0.646          | 0.551              | 10823              | 1.210            |
| MVSNet-Cas3     | 0.236        | 0.138        | 0.088        | 0.450         | 0.455          | 0.453              | 2373               | 0.322            |
| MVSNet-Cas3-Ups | 0.215        | 0.126        | 0.079        | 0.419         | 0.338          | 0.379              | 6227               | 0.676            |
| MVSNet+Ours     | 0.174        | 0.112        | 0.077        | 0.325         | 0.385          | 0.355              | 5345               | 0.492            |

Table 6: Comparison of different stereo matching methods on KITTI2015 benchmark [25].

| Methods         | All (%): D1-bg | All (%): D1-fg | All (%): D1-all | Noc (%): D1-bg | Noc (%): D1-fg | Noc (%): D1-all |
|-----------------|----------------|----------------|-----------------|----------------|----------------|----------------|
| DispNetC [23]   | 4.32           | 6.16           | 7.15           | 4.11           | 5.72           | 6.65           |
| GC-Net [15]     | 2.48           | 3.59           | 3.87           | 2.32           | 3.12           | 3.45           |
| CNRNet [19]     | 2.14           | 3.45           | 3.76           | 1.94           | 3.20           | 3.45           |
| SegStereo [3]   | 1.88           | 4.07           | 4.25           | 1.76           | 3.70           | 4.08           |
| PSMNet [3]      | 1.86           | 4.62           | 5.32           | 1.71           | 4.31           | 4.94           |
| GwcNet [8]      | 1.74           | 3.93           | 4.23           | 1.61           | 3.49           | 3.92           |
| GwcNet+Ours     | 1.59           | 4.03           | 4.30           | 1.43           | 3.55           | 4.36           |

2,373 MB to 4,093 MB and 5,345 MB, and run-time increases from 0.081 s to 0.243 s and 0.492 s.

4.2. Stereo Matching

Datasets  Scene Flow dataset [23] is a large scale-dataset containing 35,454 training and 4,370 testing stereo pairs of size $960 \times 540$. It contains accurate ground truth disparity maps. We use the Finalpass of the Scene Flow dataset [23] since it contains more motion blur and defocus and is more like a real-world environment. KITTI 2015 [25] is a real-world dataset with dynamic street views. It contains 200 training pairs and 200 testing pairs.

Implementation  In Scene Flow dataset, we extend PSMNet [3], GwcNet [8] and GANet11 [48] with our proposed cascade cost volume and denote them as PSMNet+Ours, GwcNet+Ours and GANet11+Ours. Balancing the trade-off between accuracy and efficiency, a two-stage cascade cost volume is applied, and the number of disparity hypothesis is 12. The corresponding disparity interval is set to 4 and 1 pixels respectively. The spatial resolution of feature maps increases from 1/16 to 1/4 of the original input image size. The maximum disparity is set to 192.

In KITTI 2015 benchmark [25], we mainly compare GwcNet [8] and GwcNet+Ours. For a fair comparison, we follow the training details of the original networks. The evaluation metric in Scene Flow dataset [23] is end-point-error (EPE), which is the mean absolute disparity error in pixels. For KITTI 2015 [25], the percentage of disparity outliers $D1$ is used to evaluate disparity error larger than $\max(3px, 0.05d^*)$, where $d^*$ denotes the ground-truth disparity.

Benchmark Performance  Quantitative results of different stereo methods on Scene Flow dataset [23] is shown in Table 4. By applying the cascade 3D cost volume, we boost the accuracy in all the metrics and less memory is required owing to the cascade design with smaller number of disparity hypothesis. Our method reduces the end-point-error by 0.166, 0.116 and 0.050 on PSMNet [3] (0.887 vs. 0.721), GwcNet [8] (0.765 vs. 0.649) and GANet11 [48] (0.950 vs. 0.900) respectively. The obvious improvement on $>1$px indicates that small errors are suppressed with the introduction of high-resolution cost volumes. In KITTI 2015 [25], Table 6 shows the percentage of disparity outliers $D1$ evaluated for background, foreground, and all pixels. Compared with the original GwcNet [8], the rank of GwcNet+Ours rises from 29th to 17th (date: Nov.5, 2019). Several dis-
Table 7: Comparisons between MVSNet [44] and MVSNet using our cascade cost volume with different setting of depth hypothesis numbers and depth intervals. The statistics are collected on DTU dataset [1].

| Loss Weight | Acc. (mm) | Comp. (mm) | Overall (mm) |
|-------------|-----------|------------|--------------|
| 2.0 1.0 0.5 | 0.4520    | 0.4219     | 0.4370       |
| 1.0 1.0 1.0 | 0.4521    | 0.4166     | 0.4344       |
| 0.5 1.0 2.0 | 0.4479    | 0.4141     | 0.4310       |

Table 8: Influence of loss function weight for the intermediate outputs and final prediction.

4.3. Ablation Study

Extensive ablation studies are performed to validate the improved accuracy and efficiency of our approach. All results are obtained by the three-stage model on DTU validation set [1] unless otherwise stated.

Cascade Stage Number The quantitative results with different stage numbers are summarized in Table 7. In our implementation, we use MVSNet [44] with 192 depth hypothesis as the baseline model, and replace its cost volume with our cascade design which is also consisted of 192 depth hypothesis. Note that the spatial resolution of different stages are the same as that of the original MVSNet [44]. This extended MVSNet is denoted as MVSNet-Cas, where $i$ indicates the total stage number. We find that as the number of stages increases, the overall quality first remarkably increases and then stabilizes.

Spatial Resolution Then, we study how the spatial resolution of a cost volume $W \times H$ affects the reconstruction performance. Here, we compare MVSNet-Cas3, which contains 3 stages and all the stages share the same spatial resolution, and MVSNet-Cas3-Ups where the spatial resolution increases from 1/16 to 1 of the original image size and bilinear interpolation is used to upsample feature maps. As shown in Table 5, the overall quality of MVSNet+Ours is obviously superior to those of MVSNet-Cas3 (0.453 vs. 0.355). Accordingly, a higher spatial resolution also leads to increased GPU memory (2373 vs. 5345 MB) and run-time (0.322 vs. 0.492 seconds).

Feature Pyramid As shown in Table 5, the cost volume constructed from Feature Pyramid Network [21] denoted by MVSNet+Ours can slightly improve the overall parity estimation on KITTI 2015 test set [25] is shown in Figure 7.

Figure 8: Reconstruction results of each stage. Top row: Ground truth depth map and intermediate reconstructions. Bottom row: Error maps of intermediate reconstructions.

Parameter Sharing in Cost Volume Regularization We also analyze the effect of weight sharing in 3D cost volume regularization across all the stages. As is shown in Table 7, the shared parameters cascade cost volume denoted by MVSNet-Cas3-share achieves worse performance than MVSNet-Cas3. It indicates that separate parameter learning of the cascade cost volumes at different stages further improves the accuracy.

Loss Weight The $N$ stages model contains $N - 1$ intermediate outputs and a final prediction. We conduct experiments with various combinations of loss weights of MVSNet+Ours on DTU dataset [1]. As is shown in Table 8, the proposed cascade cost volume prefers a larger loss weight at the later stages.

4.4. Run-time and GPU Memory

Table 5 shows the comparison of GPU memory and run-time between MVSNet [44] with and without cascade cost volume. Given the remarkable accuracy improvement, the GPU memory decreases from 10,823 to 5,345 MB, and the run-time drops from 1.210 to 0.492 seconds. In Table 4, we compare the GPU memory between PSMNet [3], GwcNet [8] and GANet11 [48] with and without the proposed cascade cost volume. The GPU memory of PSMNet [3], GwcNet [8] and GANet11 [48] decreases by 39.97%, 36.99% and 24.11% respectively.

5. Conclusion

In this paper, we present a both GPU memory and computationally efficient cascade cost volume formulation for high-resolution multi-view stereo and stereo matching. First, we decompose the single cost volume into a cascade formulation of multiple stages. Then, we can narrow the
depth (or disparity) range of each stage and reduce the total number of hypothesis planes by utilizing the depth (or disparity) map from the previous stage. Next, we use the cost volumes of higher spatial resolution to generate the outputs with finer details. The proposed cost volume is complementary to existing 3D cost-volume-based multi-view stereo and stereo matching approaches.

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6. Appendix

6.1. Discussion

Why Hypothesis Range is Remarkably Decreased? In Figure 9, we provide the statistics of the absolute depth errors which measure the distance between the predicted depth and its ground truth. Since there is no depth prediction at the first stage, we regard the ground-truth depth as the absolute depth errors of the first stage. As shown in Figure 9(a), the entire depth range of the first stage is approximately 500mm while the entire depth range at the second and the third stage shown in Figure 9(b) is narrowed to about 50mm which is reduced by 90% compared with the first stage. Accordingly, we can significantly reduce the hypothesis range at the second and third stages.

How to Set Hypothesis Range at Different Stages? In Figure 10, we calculate the percentage of the absolute errors less than a certain threshold (noted as inlier percentage). Hypothesis range should cover most erroneously predicted depth (or disparity) and correct them. As shown in Figure 10(a), the inlier percentage of MVSNet [44] and that of MVSNet+Ours at the first stage intersects at 5.92mm and 86%. That means if we set a hypothesis range larger than 5.92mm, we can cover more possibly correct predictions than MVSNet, since our cascade cost volume is able to correct the erroneous prediction at the later stages. On multi-view stereo data-sets, we set the hypothesis range as $32 \times 2 \times 2.5 = 160$mm which still has a large margin to be reduced.

Similarly in stereo matching, as shown in Figure 10(b), the disparity hypothesis range is set as $12 \times 2 = 24$ pixel (the intersection is 19.60 pixel), which covers the range of more erroneous predictions at the first stage compared with the original single cost volume approach.

Why Cascade Cost Volume is Memory Efficient? In multi-view stereo, the hypothesis range is able to remarkably decrease since the entire depth range is narrowed by nearly 90% (500mm vs. 50mm) since the first stage. Therefore, we can use less hypothesis planes for cost volumes in later stage. In MVSNet+Ours, we set the number of hypothesis planes in first stage as 48 whereas MVSNet [44] has 192 planes, leading to the GPU memory decrease from 10,823MB to 2,373MB. In order to improve the accuracy in subsequent stages, we increase the spatial resolution and the GPU memory increases from 2,373 MB to 4,093 MB and 5,345 MB. Although we increase the spatial resolution, the total GPU memory is deceased about 50.6% compared MVSNet and run-time is about 2 times faster shown in Figure 1 in the main paper. Similarly, in stereo matching we also decrease the GPU memory from 3,827MB to 2,699MB using our two stage cost volume.

| GwcNet     | 48 | 1  | 0.833 | 0.294 |
|------------|----|----|-------|-------|
| GwcNet-Cas2| 24, 24 | 2, 1 | 0.764 | 0.283 |
| GwcNet-Cas3| 24, 12, 12 | 2, 2, 1 | 0.737 | 0.274 |
| GwcNet-Cas4| 24, 12, 6, 6 | 2, 2, 1, 1 | 0.703 | 0.264 |

Table 9: Comparisons between GwcNet [8] and GwcNet using our cascade cost volume with different setting of the numbers of hypothesis planes and depth intervals. The statistics are collected on the test set of Scene Flow dataset [23].

Moreover, we can balance between the time (or memory) efficiency and accuracy by adopting different cascade numbers, hypothesis range and spatial resolutions.

6.2. Multi-view Stereo

In this section, we demonstrate more multi-view stereo experimental results. As shown in Figure 14, we visualize the reconstructed point cloud of MVSNet+Ours on DTU dataset [1].

6.3. Stereo Matching

Qualitative Results on Scene Flow Dataset In this section, we show several reconstruction results of PSMNet [3], GwcNet [8], GANet11 [48] and the extended model PSMNet+Ours, GwcNet+Ours, GANet11+Ours on Scene Flow dataset [23]. As is shown in Figure 12, the visual quality is improved with the replacement of our cascade cost volume.

Cascade Stage Number in Stereo Matching In this experiment, we replace the cost volume in GwcNet [8] with our proposed cascade cost volume, namely GwcNet+Ours. Note that, the experiment setting in GwcNet [8] is 64 channel concatenation volume, the spatial resolution of different stages are the same as that of the original GwcNet. The extended model with total $i_{th}$ stages is denoted as GwcNet-Cas$_i$. As is shown in Table 9, the accuracy of the extended model increases with stage increases. We can notice the details get cleaner as the stage increases in Figure 11.

Spatial Resolution in Stereo Matching We study how the spatial resolution of a cost volume affects the reconstruction accuracy and GPU memory in stereo matching. Similar to the experiment in multi-view stereo, we formulate a three-stage cost volume based on GwcNet with the spatial resolution gradually increases from $1/4 \times 1/4$ to 1 of the original input image size. In a coarse-to fine manner, the end-point-error is improved from 0.972 to 0.619. Accordingly, the GPU memory increases from 1,545MB to 3,429MB.
Figure 9: Distribution of absolute errors at different stages. We assume that the absolute errors at the 1st stage are the ground-truth depth since there is no predicted depth at this stage. The statistical results are calculated on DTU evaluation dataset [1] using MVSNet+Ours with a three-stage cost volume.

Figure 10: The percentage of the absolute errors between the prediction and the ground-truth less than a certain threshold. We demonstrate the results of MVSNet [44], GwcNet [8], and certain networks with cascade cost volume at different stages.

Table 10: The statistical results of different stages in cascade cost volume. The statistics are collected on the Scene Flow evaluation set [23] using GwcNet+Ours. The run-time is the sum of the current and previous stages and the original input size is 960×512.

6.4. Limitations and Future Works

The proposed cascade cost volume formulation benefits from decomposing the single cost volume into a cascade formulation of multiple stages. We have analyzed the effect of hypothesis range setting in Section 6.1. Although the cascade formulation is complementary to existing 3D cost-volume-based multi-view stereo and stereo matching approaches, some limitations still exist. As shown in Figure 13, GwcNet+Ours generates a biased result since the earlier stages output erroneous disparity and the hypothesis range in the next stage is not able to cover its corresponding ground truth value. Note that this case happens with little probability since the cascade cost volume formulation could correct almost erroneous predictions according to the analysis in Section 6.1 and the overall performance is also better than single cost volume models.

Currently, the hypothesis range of each pixel is identical. The future works include determine the hypothesis range for each region by incorporating semantic information but probably need a more flexible cost volume formulation.
Figure 11: Reconstruction results of each intermediate stage of GwcNet+Ours on Scene Flow test dataset [23]. From left to right: reference image and ground truth, the predicted disparity of stage1, stage2 and stage3. The zoomed areas of intermediate reconstructions is shown below its intermediate reconstructions.
Figure 12: Qualitative results on the test set of Scene Flow dataset [23]. We show the results of several representative stereo CNNs and the extended models with the proposed cascade cost volume.

Figure 13: A failed case of GwcNet+Ours on the test set of Scene Flow dataset [23]. Top row: Reference image, the prediction of GwcNet [8] and the error map of GwcNet. Bottom row: Ground Truth, the prediction of GwcNet+Ours and the error map of GwcNet+Ours. The red arrow points out the wrong prediction region.
Figure 14: Point cloud results of MVSNet+Ours on DTU evaluation dataset [1]