

# A Confidence-based Iterative Solver of Depths and Surface Normals for Deep Multi-view Stereo

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## Abstract

In this paper, we introduce a deep multi-view stereo (MVS) system that jointly predicts depths, surface normals and per-view confidence maps. The key to our approach is a novel solver that iteratively solves for per-view depth map and normal map by optimizing an energy potential based on the locally planar assumption. Specifically, the algorithm updates depth map by propagating from neighboring pixels with slanted planes, and updates normal map with local probabilistic plane fitting. Both two steps are monitored by a customized confidence map. This solver is not only effective as a post-processing tool for plane-based depth refinement and completion, but also differentiable such that it can be efficiently integrated into deep learning pipelines. Our multi-view stereo system employs multi-optimization steps of the solver over the initial prediction of depths and surface normals. The whole system can be trained end-to-end, decoupling the challenging problem of matching pixels within poorly textured regions from the cost-volume based neural network. Experimental results on ScanNet and RGB-D Scenes V2 demonstrate state-of-the-art performance of the proposed deep MVS system on multi-view depth estimation, with our proposed solver consistently improving the depth quality over both conventional and deep learning based MVS pipelines. Code is available at <https://github.com/thuzhaowang/idn-solver>.

## 1. Introduction

Dense multi-view stereo (MVS) has been a long-standing fundamental topic in computer vision. The key idea of most existing techniques is to compare the similarity of image patches at different depth hypotheses, densely matching pixels across images. While great improvement has been witnessed over decades, it is still a hard problem to accurately estimate dense geometry from posed images

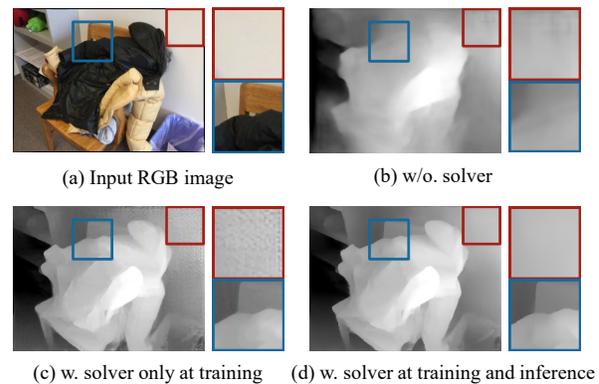


Figure 1. By integrating the proposed iterative solver into end-to-end training, our method decouples the challenging problem of estimating depth values within poorly textured regions from the initial network predictions, getting the network to focus more on reliable estimation on well textured pixels. This improves depth quality on both textured (blue) and texture-less (red) regions. Note that on texture-less areas (red box on (c)(d)), the network jointly trained with the solver only focuses on predicting reliable geometry on neighboring areas, leaving the poorly textured pixels to be resolved with the iterative solver module.

in many real-world scenarios, especially in indoor environments, where one of the most typical reasons of failure is the existence of texture-less areas (e.g. walls), which incur significant ambiguities to the matching step, as a number of different depths all result in low matching costs.

There have been various attempts to tackle this crucial problem. Global optimization [19, 5, 50] is one possible direction to resolve the ambiguities. Those methods initially assume a fixed set of superpixels and apply Markov random field with slanted-plane models. The optimization prefers globally smoothed geometry with locally planar surfaces and achieves promising performance. However, global optimization methods suffer from large computational complexity and the performance is also limited by the quality of superpixels and handcrafted dense features.

With the recent success of deep learning, learning-based

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methods have achieved great performance on datasets due to the improved quality of learned features and depth priors. Typically, a cost-volume based architecture [51, 47] is trained end-to-end with a pixelwise loss function on depths. While the ambiguities incurred by the texture-less areas still exist in the built cost volumes, several methods propose to utilize surface normals, either jointly predicted [38, 29] or online fitted [52, 33], to help train the depth predictions, aiming to implicitly enrich the network with locally planar priors by directly supervising the local structure of the predicted depth map. However, it is still a difficult problem to successfully learn such priors and accurately predict depths on texture-less areas directly from the ambiguous cost volumes built on warped patches.

In this paper, we propose a novel deep multi-view stereo system that decouples the locally planar priors from the cost volume based depth/normal prediction networks. The key to our proposed system is a differentiable confidence-based solver that iteratively solves for depth map and normal map by optimizing an energy potential that prefers locally planar surfaces. For each optimization iteration, the solver updates depth map by propagating from neighboring pixels with slanted planes, and updates normal map with local probabilistic plane fitting. A customized confidence map can be used to monitor both two steps.

Our deep MVS system firstly predicts depth, normal and confidence jointly and then applies multiple optimization steps of our depth-normal solver upon the initial predictions. Those multiple steps enable long-range propagation of reliable depths and normals. The whole system can be trained end-to-end, guiding the depth/normal network to focus more on confident depth/normal predictions on textured areas and leave the poorly textured regions to be resolved with the solver. For the solver module, a hybrid confidence map combining the deep confidence prediction and the conventional geometric reprojection check can be used to stabilize the optimization process at inference.

The proposed system combines the advantages of slanted-plane models [4] and learning-based techniques. With end-to-end training, the initial depth prediction is guided to focus only on reliable estimation over partial regions rather than the whole image (as shown in Fig. 1). Experimental results on ScanNet and RGB-D Scenes V2 show that our novel deep MVS achieves state-of-the-art performance in terms of accuracy on depths and surface normals, with the proposed solver consistently improving the depth quality over both conventional and deep MVS pipelines.

## 2. Related Work

**Multi-view Stereo.** Reconstructing 3D models from posed images has been widely studied over decades. Early methods [30, 12, 46] utilize volumetric optimization. Later attempts [53, 14, 6, 20, 41] reconstruct per-view depth

maps by comparing cross-view image patches, which becomes the de facto approach of modern multi-view stereo pipelines. Recent advances include employing superpixels [39], post-refinement [27, 28], and advanced propagation checkerboards [13, 48, 49], etc. With the success of deep learning, a number of learning-based techniques are proposed to tackle the problem. While several methods learn to directly predict 3D geometry as grids [25, 24], point clouds [7] and TSDF [35], per-view depth map estimation is still the top choice of most approaches [47, 51, 23, 32, 21, 29, 33, 10, 36] due to its robustness and flexibility. Most of those methods follow the spirit of conventional approaches [14, 6] and train a cost volume based neural network. Some of the methods [21, 10, 36] also integrate temporal information with recurrent networks. However, direct prediction over poorly textured areas have been one of the main difficulties of most approaches relying on cost volumes. An exception of this is DELTAS [43], which proposes to learn interest points and perform triangulation and densification over sparse points. In this work, we also focus on per-view depth estimation and introduce an end-to-end MVS system equipped with a novel iterative solver, which implicitly decouples depth prediction over texture-less areas from the cost-volume based network.

**Confidence Estimation.** Accurately estimating per-view depth map confidence is beneficial to 3D reconstruction pipelines. Early confidence measures such as matching cost, peak ratio and maximum likelihood are extensively studied in [18, 22]. Local smoothness can also contribute to the confidence measurement of the stereo problem [44, 17]. Recently, learning-based methods [42, 37] are proved to be effective on confidence estimation. Most related to us, [28] exploits the counter map acquired from the geometric consistency check for deep confidence prediction. In our MVS system, we combine deep confidence estimation and geometric consistency check together to get our final confidence map, which monitors the solver at inference.

**Depth-Normal Constraints.** As depths and surface normals are naturally coupled by local plane fitting, joint depth-normal constraints are widely employed. Markov random fields with slanted-plane models were initially introduced in [4], and were later used in many stereo techniques [19, 5, 50]. Those methods operate on superpixels and prefer locally planar surfaces. [6] proposed to employ slanted support windows in its PatchMatch stereo framework, coupling the depth propagation with the randomly initialized per-pixel surface normal. [15] further introduce a minimal-surface regularization method. [45] propose to embed bilateral filtering in the plane fitting process to encourage locally planar structures of the output depth map. Recent learning-based methods also exploit surface normals to help train the depth prediction. While [11, 38, 29] jointly predict depths

and surface normals together to benefit from multi-task feature learning, recent literature [52, 33] adopts online fitting. In [55], a surface normal network is trained to help solve for dense depth map from sparse depth observations. Different from prior works, our method explicitly exploits depth-normal constraints via a differentiable iterative solver.

### 3. An Iterative Depth-Normal Solver

The key to our deep multi-view stereo system is a confidence-based iterative depth-normal solver module, which solves for per-view depth map and normal map from the initial predictions. Specifically, we assume locally planar structure of the depth map and couple the normal map within our optimization scheme.

#### 3.1. Energy Formulation

Our energy potential  $E_{total}$  consists of a data term  $E_{data}$  and a plane-based structural term  $E_{plane}$ , with the hyperparameter  $\alpha$  weighting the two terms:

$$E_{total} = \alpha E_{data} + E_{plane}, \quad (1)$$

The data term regularizes the output geometry with respect to the given initial geometry. Take  $d_i, n_i$  as the per-pixel depth and surface normal respectively, and  $c_i$  as the per-pixel confidence. Denote the initial depth and surface normal as  $\hat{d}_i$  and  $\hat{n}_i$ . The data term is written as follows:

$$E_{data} = \sum_i c_i (d_i - \hat{d}_i)^2 + \sum_i c_i \|n_i - \hat{n}_i\|^2. \quad (2)$$

The plane-based structural term  $E_{plane}$  enforces the output depth and surface normal to agree with the local planar assumption with respect to neighboring geometry. Let  $(x_i, d_i, n_i)$  and  $(x_j, d_j, n_j)$  denote the 2D coordinate, depth and surface normal of the current pixel and its neighboring pixel respectively.  $P(x, d, n)$  denotes the slanted plane at position  $x$  generated by spanning a plane from the corresponding 3D points recovered from  $d$  and  $x$  with the surface normal  $n$ . Our plane-based structural energy can be formulated in either of the two below directions:

- $E_{j \rightarrow i}$ . The sum (over each pixel) of distance functions between the 3D point recovered from  $d_i$  and  $x_i$  at the current pixel  $i$  and the slanted plane  $P(x_j, d_j, n_j)$  generated at its neighboring pixel  $j$ .  $d_{j \rightarrow i}$  denotes the projection of the slanted plane  $P(x_j, d_j, n_j)$  at pixel  $i$ .
- $E_{i \rightarrow j}$ . The sum (over each pixel) of distance functions between the slanted plane  $P(x_i, d_i, n_i)$  generated at the current pixel  $i$  and the 3D point recovered from  $x_j$  and  $d_j$  at its neighboring pixel  $j$ .  $d_{i \rightarrow j}$  denotes the projection of the slanted plane  $P(x_i, d_i, n_i)$  at pixel  $j$ .

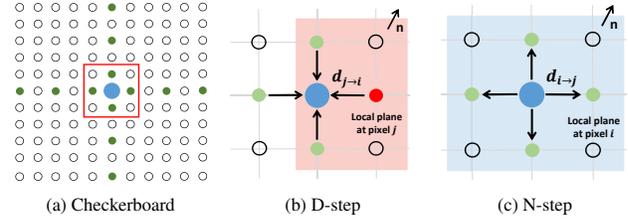


Figure 2. Illustration of the proposed solver. (a) we use a sparse checkerboard to define the neighborhood of each pixel, which enables large receptive fields and efficient computation. (b) In the D-step, we update depth map by propagating from neighboring pixels with slanted planes. (c) In the N-step, we update normal map with local probabilistic plane fitting.

For the definition of neighboring pixels, we can either use a sparse checkerboard [13, 48] (as in Fig. 2(a)) or randomly sample sparse points within a fixed window. This enables efficient long-range propagation of the neighboring geometry. In both formulations of the structural energy the contribution of each pixel is also monitored by the per-pixel confidence  $c_i$ . Motivated by the effective formulation in the bilateral filtering techniques [2, 3], we also weight the contribution of the neighboring pixels with the edge-aware bilateral affinity, denoted as  $w_{ij}$ :

$$w_{ij} = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma_x^2} - \frac{\|I_i - I_j\|^2}{2\sigma_c^2}\right), \quad (3)$$

where  $I_i$  denotes the RGB value at each pixel. While we use RGB colorspace here for simplicity, the weight can be easily extended to YUV space, as employed in [2, 3].

#### 3.2. Iterative Subproblem Optimization of Depths and Surface Normals

We aim to minimize the total energy with an effective, parallelized and differentiable approximation. To parallelize the computation, we assume fixed neighboring geometry and solve for each pixel individually at each update step. Since depths and surface normals are non-linearly coupled when propagating from neighboring pixels due to the perspective projection of the slanted planes, closed-form solution can not be acquired for the whole energy potential with depths and normals both considered in the data term<sup>1</sup>.

Our proposal is to iteratively solve for depths and surface normals. As shown in Figure 2(b)(c), Each iteration is further divided into two steps of subproblem optimization, where we solve for depths/normals individually with the other variables (normals/depths) fixed. Those two subproblems can all have closed-form solutions. Furthermore, we alternate between the two plane-based structural term formulations to better fit each sub-problem, acquiring a

<sup>1</sup>If only the surface normal data term is considered, closed-form solution can be derived by substitution of variables.

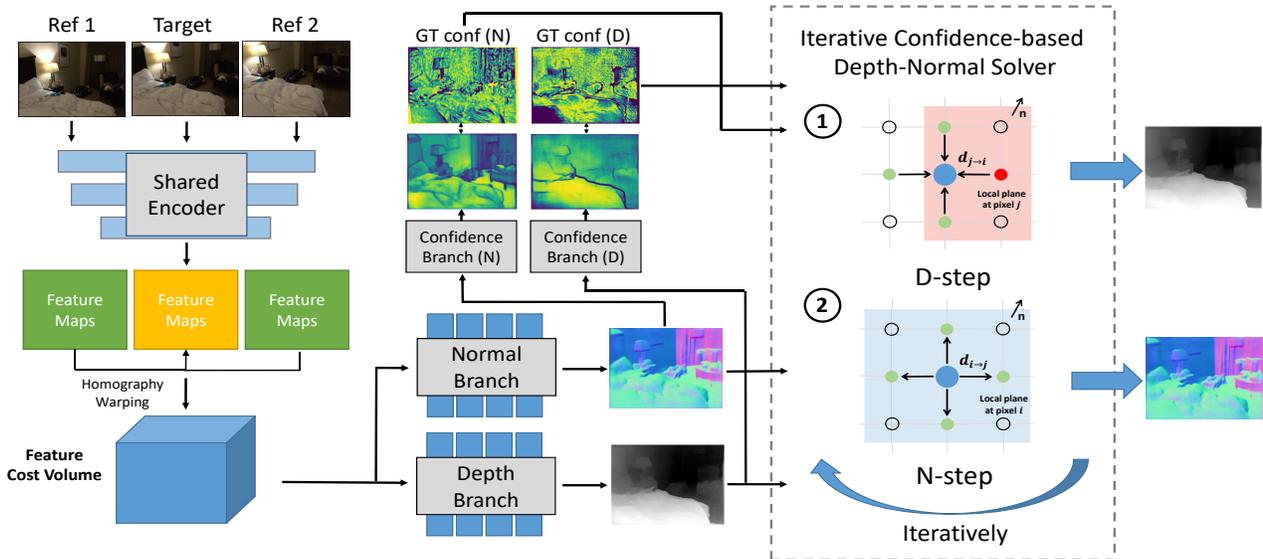


Figure 3. An overview of our deep multi-view stereo (MVS) system. First, We feed the target image and multiple reference images into a shared encoder to extract per-view deep image features, which are used to build a feature cost volume. Then, we jointly predict depth, surface normal and confidence from the cost volume with 3D CNNs and 2D dilated CNNs [54]. Finally, the confidence-based depth-normal solver is applied over the predicted depths and surface normals iteratively to get the final output. The whole system can be trained end-to-end. At training, a groundtruth confidence map computed by the relative depth error is used to help guide the initial prediction to focus on estimating reliable geometry on textured areas. Note that the inputs of the confidence branch are simplified for better visualization.

decoupled linear system algebraically for both steps, thus making the gradients of the whole solver tractable.

**Depth Update (D-step).** In the depth update step, we fix the surface normal map and solve for the optimal depth map that minimizes the depth energy  $E_d$  as follows:

$$\min_d E_{total} = \min_d E_d \quad (4)$$

$$E_d = \alpha \sum_i c_i (d_i - \hat{d}_i)^2 + \sum_i \sum_{j \in N(i)} c_j w_{ij} (d_i - d_{j \rightarrow i})^2, \quad (5)$$

where  $N(i)$  denotes the defined neighborhoods of the pixel  $i$ . We employ  $E_{j \rightarrow i}$  as the plane-based structural term and computes the L2 distance between the optimized depth and the propagated depth  $d_{j \rightarrow i}$ . As previously discussed, we assume fixed neighboring geometry, so the propagated depth  $d_{j \rightarrow i}$  here is the projection of the slanted plane  $P(x_j, \hat{d}_j, \hat{n}_j)$  at pixel  $i$ . Compared to  $E_{i \rightarrow j}$  which only uses one surface normal query at the pixel itself, employing  $E_{j \rightarrow i}$  improves robustness to outliers in the initial surface normal map, enabling the solver to utilize surface normals in all neighboring pixels. We can derive closed-form optimal depth by setting the first-order derivative of  $E_d$  to zero.

**Surface Normal Update (N-step).** In the surface normal update step, we fix the depth map and solve for the optimal

surface normal that minimizes the surface normal energy  $E_n$  as follows:

$$\min_n E_{total} = \min_n E_n \quad (6)$$

$$E_n = \alpha \sum_i c_i \|n_i - \hat{n}_i\|^2 + \sum_i \sum_{j \in N(i)} c_j w_{ij} D_n(d_j, P(x_i, d_i, n_i)). \quad (7)$$

$D_n$  is a distance function between the depth  $d_j$  at neighboring pixels and the slanted plane  $P(x_i, d_i, n_i)$  at pixel  $i$ . The plane equation is computed from the depth  $d_i$  updated in the last step and the surface normal  $n_i$  being optimized, forming a local probabilistic plane fitting problem. Note that simply employing L2 distance between  $d_j$  and  $d_{i \rightarrow j}$  as in the D-step will result in a non-quadratic surface normal energy due to the perspective projection during plane-based propagation. Instead, we can parameterize the surface normal as  $n = (a, b, -1)$  and utilize the algebraic form of the plane equation to acquire a quadratic energy, where 2 linear equations can be acquired by setting the first-order derivatives to zero, being sufficient to solve the 2-DoF surface normal  $n_i$  in closed form<sup>2</sup>.

## 4. Deep Multi-view Stereo System

Based on the confidence-based iterative solver, we propose a deep multi-view stereo system that jointly predicts

<sup>2</sup>Please refer to our supplementary material for more details.

per-view depths, surface normals and confidence maps. Figure 3 shows an overview of the proposed system.

#### 4.1. Estimating Initial Depths and Surface Normals

As our work does not focus on the network architectures, we mostly follow prior works [23, 29] to build the cost-volume based multi-view depth-normal network. First, the target image and multiple reference images are fed into a shared neural network encoder respectively to acquire per-view deep image features. Then, we apply plane sweeping on feature maps to build a feature cost volume. 3D CNNs and 2D dilated CNNs [54] are applied over the cost volume to aggregate and regularize the cost information. The depth maps are then regressed using the soft argmin operator from the final cost volume. The normal branch follows the design of [29], which concatenates the world coordinate volume with the feature cost volume, and uses cost volume slices to estimate the surface normal.

For the confidence estimation, multiple sources are utilized to facilitate the effective confidence regression, including intermediate feature maps, cost volumes, and the predicted depths/normals. We feed them into two mini-networks which consist of several dilated convolutions and a final sigmoid activation, to estimate the confidence for depth and normal respectively. Please refer to our supplementary material for details on the network architecture.

To train the network, we use smoothed L1 loss for depth and normal, and cross-entropy loss for confidence. The groundtruth confidence maps  $c_{dgt}$  and  $c_{ngt}$  are computed from the relative depth error  $e_{rel}$  and normal angle error  $e_{ang}$ :  $c_{dgt} = \max(1.0 - \gamma_1 e_{rel}, 0.0)$  and  $c_{ngt} = \max(1.0 - \gamma_2 e_{ang}, 0.0)$ , where  $\gamma_1, \gamma_2$  are hyperparameters.

#### 4.2. Integrating the Proposed Solver

After acquiring the initial predictions, we employ our solver module over the initial depth map and surface normal map. Specifically, D-step and N-step are applied iteratively for multiple iterations. We use 5 iterations for training and more steps can be used at inference. Multiple iterations lead to more accurate approximation of the optimal depth and surface normal under the local planar assumption. Moreover, since the plane-based propagation is limited by the window size of the checkerboard, using multiple iterations enables long-range propagation from reliable pixels. Empirically we find that improving the number of iterations at inference does lead to better depth quality (See Table 6).

Since all operations in the solver are differentiable, the whole system can be trained end-to-end, where the loss on the final solved geometry can be back-propagated into the network for training initial depth/normal predictions. At the training stage, we apply the depth loss and normal loss both on the initial predictions and the final solved geometry.

The end-to-end training of the system brings up several

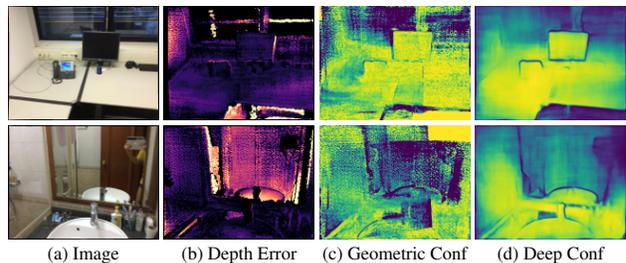


Figure 4. Visualization on different confidence maps. The relative depth error (b) is used to compute the groundtruth confidence. While the confidence acquired by geometric consistency check (c) is more accurate, the deep confidence (d) is complete and acts as a supplements to the geometric confidence at inference.

advantages. First, the solver can be considered as a closed-form refinement step to the initial depth/normal predictions, which improves robustness to noise and outliers. Moreover, the plane-based structural term favors locally planar surfaces, which is particularly beneficial on poorly textured regions and occluded areas in indoor environments, where cost-volume based approaches struggle to estimate accurate geometry due to large ambiguity. Integrating the proposed solver into our end-to-end deep MVS system eliminates the necessity for the network to handle pixels in extremely texture-less regions, since it can be left to the propagation steps of the solver at inference. This promotes our network to only focus on reliable estimation on textured areas, which largely releases the learning burden. As shown in Figure 1, this mechanism improves the depth quality significantly on both textured and texture-less regions.

To better enrich the network with such behaviors, at training we apply the iterative solver with the groundtruth depth/normal confidence map, which is computed by comparing the error of the depth/normal map with the groundtruth depth/normal. We empirically observe that high-quality confidence map for the solver is needed during training. Only using the jointly predicted confidence map at training cannot successfully enrich the initial predictions with the aforementioned nice property.

#### 4.3. Inference

At inference, we use the trained network to predict initial depths, surface normals and confidence maps. The predicted confidence can be used in the iterative solver with the initial depth map and normal map as input. To further improve the quality of the depth confidence, we also utilize a cross-view geometric consistency check over the predicted depth maps at multiple views to acquire a geometric confidence. The target depth is reprojected and compared with the reference depths to compute the relative depth error, which is then converted into geometric confidence. If multiple reference images are available, we take the minimum over computed confidence maps to get a “strict” confi-

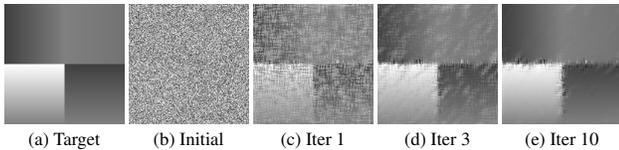


Figure 5. Visualization on the optimization process of the proposed depth-normal solver for a synthetic proof-of-concept experiment.

dence, which reduces the number of false-positive high confidence pixels. As shown in Figure 4, while the geometric confidence is often more accurate, the deep confidence is complete under occlusions and small overlaps, which can serve as a good supplement in practice. A hybrid confidence map can be acquired by multiplication of the deep confidence and the geometric confidence, which is used in the iterative solver to produce the final output geometry.

## 5. Experiments

### 5.1. Implementation Details

We use the ScanNet dataset [9] to train our system. The official training split is adopted. Three views from one sequence with a fixed frame interval 20 forms a training data sample. The initial depth and normal network is firstly trained with 15 epochs, then integrated with the solver and trained end-to-end for another 10 epochs. We use the Adam optimizer [26] with learning rate  $1e-4$  and batch size 24 on 4 Nvidia V100 GPUs. For the solver, we define the neighborhood by offsetting each coordinate with 1, 3, 5, 10 pixels horizontally and vertically, forming 16 valid entries of the propagation checkerboard (as illustrated in Figure 2(a)).

**Time efficiency.** A direct implementation in PyTorch takes 14ms for each iteration on a Nvidia V100 GPU. Implementing a CUDA C++ kernel can lead to 0.9ms/iter (15x speed-up) over a 4-Megapixel image, which is nearly negligible compared to the the backbone network.

### 5.2. Validating the Solver Module

We first perform a validation check on the effectiveness of the proposed solver module under a non-learning setup, where the solver serves as a post-processing tool for depth refinement and completion. We start with a synthesis case where four different  $100 \times 100$  planar regions are projected onto a  $200 \times 200$  image. For the initial input, the geometry of each pixel has 95% probability to be substituted with random noise, simulating unreliable pixels. Figure 5 shows qualitative results of applying the iterative solver on the input geometry. With the iterative optimization of depths and normals, the geometry is gradually refined to be close to the groundtruth target, demonstrating that our proposed solver successfully integrate locally planar priors into the optimization. We further test the solver on real outdoor data acquired from AdelaideRMF dataset [1], which is widely used for multi-structure fitting methods [16, 34]. Specifi-

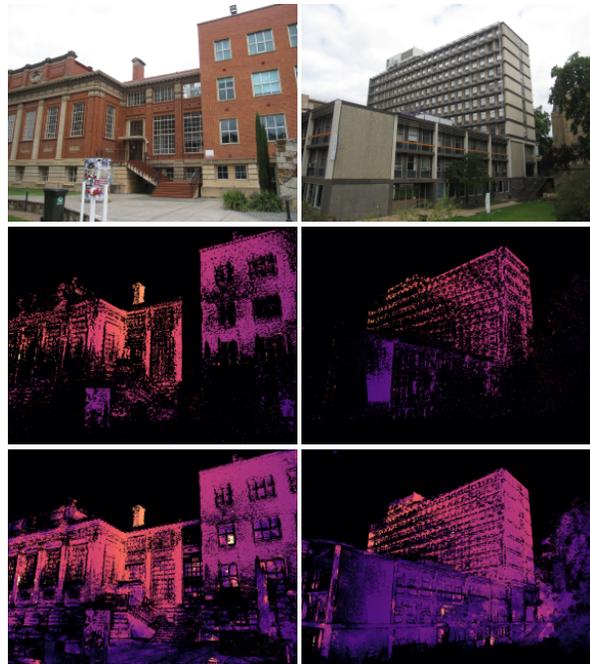


Figure 6. Results on applying the proposed solver over sparse reconstructions from COLMAP [40, 41]. **Top row:** input image. **Middle row:** initial sparse depth map acquired from COLMAP. **Bottom row:** output depth after applying the proposed solver.

cally, we apply the iterative solver over the depth map acquired from the sparse reconstruction of COLMAP [40, 41]. Results are shown in Figure 6. Our proposed solver successfully complete the sparse input with reasonably correct output, demonstrating the effectiveness of the module.

### 5.3. Experiments on Multi-view Stereo

To compare our proposed deep MVS system with leading approaches, we evaluate our method on well-established benchmarks including ScanNet’s official test split [9] and RGB-D Scenes V2 dataset [31]. Both datasets include challenging indoor scenes with many poorly textured regions. Quantitative results on multi-view depth estimation are shown in Table 1 and Table 3, where our system surpasses all existing state-of-the-art methods by a large margin on both datasets. Qualitative results in Figure 7 also demonstrate great improvement of our proposed system. Our method not only produces accurate depth map, but also successfully handles fine details around boundaries. We further evaluate the estimated surface normal for our deep MVS system. Results are shown in Table 2, where we again achieves state-of-the-art performance on ScanNet dataset [9]. Qualitative visualizations in Figure 9 clearly show the improvement of our method. Finally, we show visualizations of reconstructed models after TSDF fusion [8] in Figure 8. Our method produces visually more appealing reconstructions compared to strong baseline methods [23, 43].

Method	Abs Rel	Abs Diff	Sq Rel	RMSE	RMSE log	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
MVDepth [47]	0.1053	0.1987	0.0634	0.3026	0.1490	0.8817	0.9723	0.9924
MVDepth (FT)	0.1014	0.1891	0.0476	0.2850	0.1390	0.8930	0.9764	0.9941
GP-MVS [21]	0.0920	0.2283	0.0644	0.4436	0.1560	0.8918	0.9629	0.9918
GP-MVS (FT)	0.0787	0.2008	0.0518	0.4009	0.1394	0.9134	0.9643	0.9931
NeuralRGBD [32]	0.0871	0.1710	0.0409	0.2693	0.1324	0.9150	0.9785	0.9925
CNM [33]	0.1119	0.2101	0.0510	0.2970	0.1485	0.8686	0.9724	0.9930
DPSNet [23]	0.1164	0.1992	0.0606	0.3065	0.1602	0.8569	0.9575	0.9884
DPSNet (FT)	0.0910	0.1807	0.0410	0.2697	0.1291	0.9008	0.9787	0.9952
NAS [29]	0.0795	0.1597	0.0323	0.2357	0.1112	0.9284	0.9862	0.9966
DELTA [43]	0.0738	0.1380	0.0245	0.2051	0.1021	0.9473	0.9890	0.9976
Ours	<b>0.0665</b>	<b>0.1281</b>	<b>0.0240</b>	<b>0.1995</b>	<b>0.0990</b>	<b>0.9489</b>	<b>0.9896</b>	<b>0.9978</b>

Table 1. Quantitative comparisons between our method and state-of-the-art deep MVS methods on ScanNet dataset [9]. All the methods use sequences of length 3 and fixed reference interval 20 for testing, except GP-MVS [21] and NeuralRGBD [32], which directly use the whole sequence. Since [47, 21, 23] were not initially trained on ScanNet, we also report the results after finetuning, denoted as “FT”.

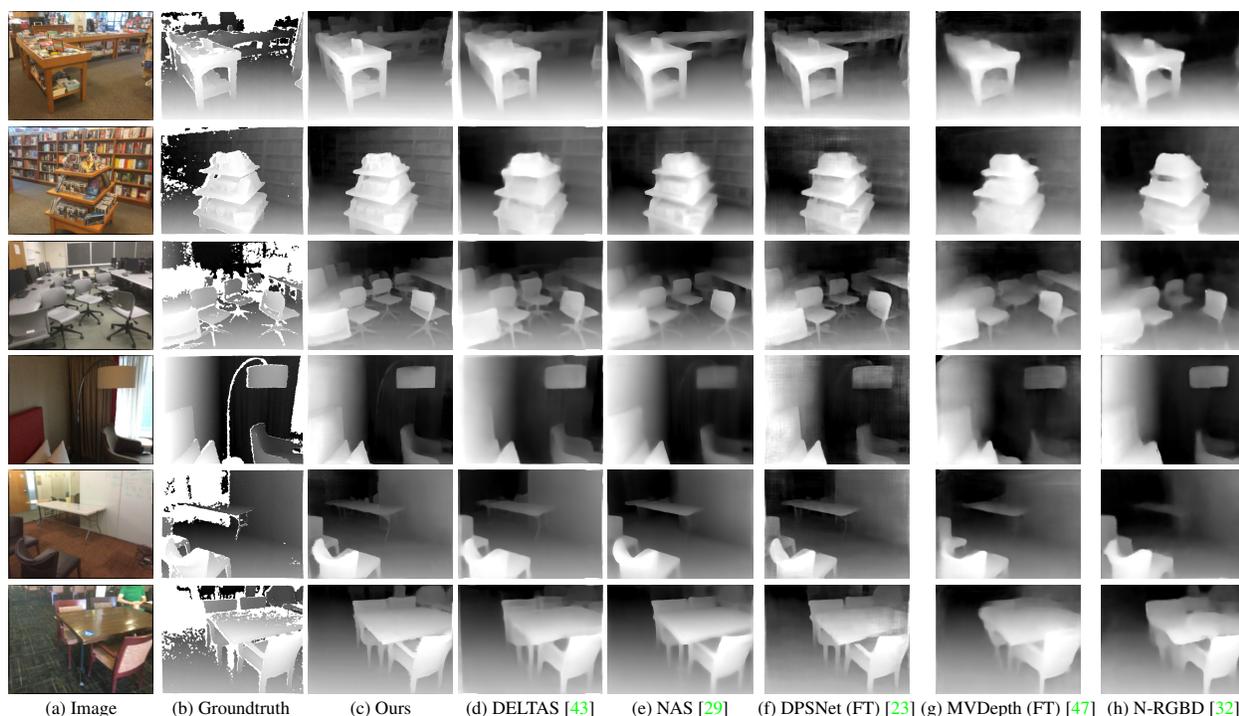


Figure 7. Qualitative results of multi-view depth estimation on ScanNet [9]. **Better viewed when zoomed in.**

Method	Mean	Median	11.25°	22.5°	30°
CNM [33]	27.92	22.12	27.43	52.16	63.44
NAS [29]	24.12	18.02	31.59	60.20	69.45
Ours	<b>22.30</b>	<b>16.75</b>	<b>34.80</b>	<b>64.39</b>	<b>75.11</b>

Table 2. Quantitative comparisons of surface normal estimation between our method and state-of-the-art methods [33, 29].

Method	Abs Rel	Abs Diff	Sq Rel	RMSE	$\delta < 1.25$
MVDepth [47]	0.0885	0.1467	0.0314	0.2313	0.9184
GP-MVS [21]	0.1087	0.1514	0.0827	0.2873	0.9170
N-RGBD [32]	0.0995	0.1530	0.0352	0.2361	0.9233
CNM [33]	0.1350	0.1873	0.0484	0.2619	0.8667
DPSNet [23]	0.0771	0.1290	0.0234	0.2045	0.9401
NAS [29]	0.0732	0.1241	0.0198	0.1893	0.9576
DELTA [43]	0.1065	0.1528	0.0299	0.2138	0.9156
Ours	<b>0.0698</b>	<b>0.1130</b>	<b>0.0194</b>	<b>0.1770</b>	<b>0.9681</b>

Table 3. Quantitative comparisons between our method and state-of-the-art deep MVS methods on RGB-D Scenes V2 dataset [31].

## 5.4. Ablation Studies

We perform several ablation studies to further understand the behaviors of the proposed solver. All ablation studies are conducted on ScanNet [9]. To study the contribution of the depth-normal solver with its post process-

ing and end-to-end joint training, we train a baseline with the same network architecture completely without the proposed solver, which does not benefit from joint training. For

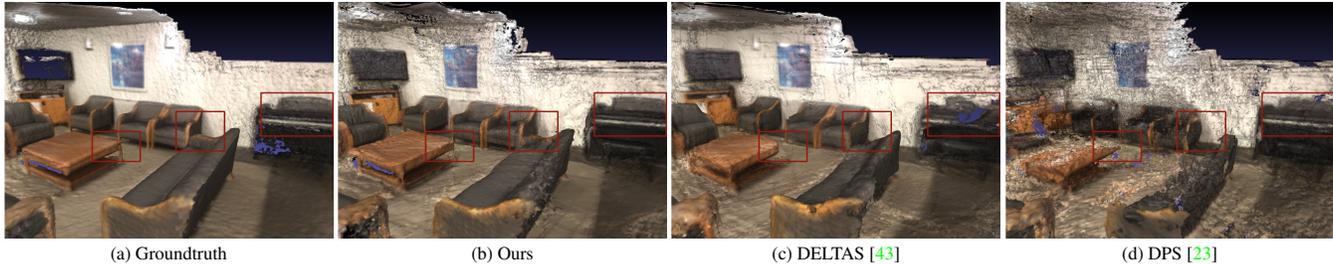


Figure 8. Visualization of our reconstruction results compared to DELTAS [43] and DPS [23]. **Better viewed when zoomed in.**

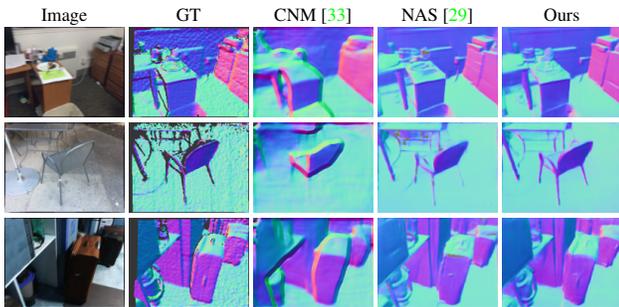


Figure 9. Qualitative results of surface normal estimation on ScanNet [9]. Refer to supp. for higher-resolution images.

comparison, we also apply the solver to refine the baseline’s output with the hybrid confidence map at inference. Three conclusions can be acquired from the results shown in Table 4: 1) As a post-processing tool, the proposed solver consistently improves the output of the network no matter whether the network is jointly trained. 2) The joint training improves the quality of the estimated initial depth (0.0735  $\rightarrow$  0.0711). This is because joint training gets the network to focus more on reliable estimation on well textured areas, which largely releases the learning burden. 3) With end-to-end joint training, the performance gain of applying the solver module at inference increases. This agrees with our assumption that during end-to-end training, the network is guided to output initial geometry that well fits the subsequent solver module.

In addition, we also study the design choices on the confidence map. Table 5 shows the results. We observe that geometric confidence is more effective than the estimated deep confidence. Although the performance gain of including the deep confidence is not significant, the deep confidence is complete and will not be affected by occlusions or small overlaps, which can serve as a good supplements for geometric confidence in practice. Furthermore, we study the effects of different number of reference views during geometric consistency check and different number of iterations at inference. Table 6 shows the results, which indicate that improving the number of iterations consistently improve the final depth quality. However, as currently we take the minimum confidence over all reference frames to get a “strict” depth confidence, adding views will only result in slight performance gain. More advanced confidence based on multi-view depth fusion is left for future work.

Method	Abs Rel	RMSE	$\delta < 1.25$
Baseline	0.0735	0.2169	0.9359
Baseline + post	<b>0.0720</b>	<b>0.2148</b>	<b>0.9378</b>
Joint train w/o post	0.0711	0.2121	0.9384
Joint train + post	<b>0.0665</b>	<b>0.1995</b>	<b>0.9489</b>

Table 4. Ablation studies on the contribution of the solver used at post-processing and end-to-end joint training. “post” indicates using the solver to post-process the depth map with 10 iterations.

Method	Abs Rel	RMSE	$\delta < 1.25$
Joint train w/o post	0.0711	0.2121	0.9384
Groundtruth conf	0.0599	0.1931	0.9604
Deep conf only	0.0692	0.2040	0.9421
Geometric conf only	0.0667	0.2001	0.9486
Deep + geometric conf	<b>0.0665</b>	<b>0.1995</b>	<b>0.9489</b>

Table 5. Studies on the choices of different confidence maps.

View/Iter	1 iter	5 iters	10 iters	25 iters
1 view	0.0694	0.0680	0.0675	0.0670
2 views	0.0690	0.0672	0.0665	0.0659
4 views	0.0688	0.0669	0.0662	0.0655

Table 6. Ablation studies on the effects of different number of views used during geometric consistency check and different number of iterations at inference. Abs Rel is reported for each entry.

## 6. Conclusion

In this work, we present a deep MVS system with a novel confidence-based iterative depth-normal solver. We formulate an energy potential that favors locally planar surfaces and propose to perform iterative subproblem optimization over depths and surface normals in turn. Not only is the solver able to serve as a post-processing tool for plane-based depth refinement and completion, but it is also in closed form such that it can be integrated into our deep MVS system with end-to-end joint training. Future directions include advanced confidence estimation and spatial-temporal plane-based propagation.

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