RGBD-Net: Predicting color and depth images for novel views synthesis

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Abstract

We propose a new cascaded architecture for novel view synthesis, called RGBD-Net, which consists of two core components: a hierarchical depth regression network and a depth-aware generator network. The former one predicts depth maps of the target views by using adaptive depth scaling, while the latter one leverages the predicted depths and renders spatially and temporally consistent target images. In the experimental evaluation on standard datasets, RGBD-Net not only outperforms the state-of-the-art by a clear margin, but it also generalizes well to new scenes without per-scene optimization. Moreover, we show that RGBD-Net can be optionally trained without depth supervision while still retaining high-quality rendering. Thanks to the depth regression network, RGBD-Net can be also used for creating dense 3D point clouds that are more accurate than those produced by some state-of-the-art multi-view stereo methods.

1. Introduction

Novel View Synthesis (NVS), also called Image-Based Rendering (IBR), is a long-standing problem that has applications in free-viewpoint video, telepresence, and mixed reality [40]. NVS is a problem where visual content is captured from one or several reference views and synthesized for an unseen target view. The problem is challenging since mapping between views depends on the 3D geometry of the scene and the camera poses between the views. Moreover, NVS requires not only propagation of information between views but also hallucination of details in the target view that are not visible in reference image due to occlusions or limited field of view.

Early NVS methods produced target views by interpolating in ray [23] or pixel space [7]. They were followed by works that leveraged certain geometric constraints such as epipolar consistency [3] for depth-aware warping of the input views. These interpolation based methods suffered from artifacts arising from occlusions and inaccurate geometry. Later works tried to patch the artifacts by propagating depth values to similar pixels [4] or by soft 3D reconstruction [34]. However, these approaches cannot leverage depth to refine the synthesized images or deal with the unavoidable issues of temporal inconsistency.

More recently, functional representation methods [42, 29, 26] have employed deep neural networks to learn implicit scene representations from a large set of observations of a specific scene. Although these methods produce impressive novel views, dedicated per-scene training is required to apply the representation to a new scene. Another research direction [58, 28, 9] uses a small number of observations at each training step. While the quality of the generated novel views of these methods is worse than those produced by the function-based representation methods, they generalize to unseen data without fine-tuning or retraining.

In this paper, we adopt the best of both approaches and develop a method that renders high-quality novel views from an unstructured set of reference images, without needing per-scene training. We propose a new method called RGBD-Net that produces both color (RGB) and depth (D) images of the unseen target view. As illustrated in Fig. 1, RGBD-Net includes two main modules: a depth regression network \( R \) and a depth-aware generator network \( G \). The first module estimates the target view depth map and the second module produces photo-realistic novel views using the regressed depth maps. Our experiments show that it generalizes well to arbitrary scenes without the need for per-scene optimization. To summarize, the main contributions of our work are:

- Adaptive depth scaling that enables producing photo-realistic novel views with and without per-scene optimization.
- A spatial-temporal module that allows RGBD-Net to produce a smooth sequence of rendered novel views along a continuous camera path.
- State-of-the-art results in novel view synthesis on three
challenging large-scaled 3D datasets [1, 53, 21].

Source code and neural network models will be made publicly available upon publication of the paper.

2. Related Work

In the following, we discuss different methods of novel view synthesis. For an extensive discussion of view synthesis, we would like to refer to Tewari et al. [45].

Novel view synthesis. Early works on view synthesis with deep learning often use a Plane Sweep Volume (PSV) [10] for novel view synthesis. Each input image is projected onto successive virtual planes of the target camera to form a PSV. Kalantari et al. [18] calculates the mean and standard deviation per plane of the PSV to estimate the disparity map and render the target view. RGBD-Net proposes a hierarchical depth regression network that predicts the depth map of the novel view in a coarse-to-fine manner. Moreover, our work focuses on solving the problem of view synthesis using unstructured inputs which poses a more demanding challenge than using grid-sampled views captured by the light-field camera. Extreme View Synthesis (EVS) [9] builds upon DeepMVS [16] to estimate a depth probability volume for each input view that is then warped and fused into the target view. Rather than estimating the depth maps of the source images, we train RGBD-Net to predict the depth map at the target view directly and then refine the warped novel images using a depth-aware generator network.

Perhaps, the closest work to RGBD-Net is the recently published Free View Synthesis (FVS) by Riegler et al. [36]. In this work, they use a structure-from-motion method [38] to reconstruct a 3D mesh of the scene for creating an incomplete depth map for the target view. They also propose a recurrent blending network to refine the warped novel views. RGBD-Net estimates a complete depth map to refine the warped novel image.

Neural scene representations. Recent geometric deep learning methods learn to deal with 3D scenes using various types of 3D representations such as multi-layered representation [58, 43, 48, 11], voxel-grids [27, 41], meshes [46], point-clouds [51, 2], and function-based [31, 26, 24, 2, 29, 30, 42].

A significant number of works [58, 43, 48, 11] on view synthesis represent the 3D scene by Multiple Plane Images (MPIs). Each MPI includes multiple RGB-α planes, where each plane is related to a certain depth. The target view is generated by using alpha composition [35] in the back-to-front order. Zhou et al. [58] introduce a deep convolutional neural network to predict MPIs that reconstruct the target views for the stereo magnification task. Later work by Flynn et al. [11] considerably improves the quality of synthesized images in the light-field setups. They propose a novel network with a regularized gradient descent method to refine the generated images gradually. Local Light Field Fusion (LLFF) [28] introduces a practical high-fidelity view synthesis model that blends neighboring MPIs to the target
view. The input to the MPI-based methods is also PSVs. However, those PSVs are constructed on a fixed range of depth values. The proposed RGBD-Net builds multi-scale PSVs which use adaptive sampled depth planes.

Grid-based representations are similar to the MPI representation, but are based on a dense uniform grid of voxels. This representation have been used as the basis for neural rendering techniques to model object appearance [27, 41]. Sitzmann et al. [41] learns a persistent 3D feature volume for view synthesis and employs learned ray-marching. Neuronal Volumes [27] is an approach for learning dynamic volumetric representations of multi-view data. The main limitation of grid-based methods is the required cubic memory footprint. The sparser the scene, the more voxels are empty, which wastes model capacity and limits output resolution. We propose a memory efficient multi-scale PSV representation which assigns dynamic depth planes per-pixel.

Recent works [51, 2, 22] on view synthesis have also employed the point-based representation to model 3D scene appearance. A drawback of the point-based representation is that there might be holes between points after projection to the screen space. Aliev et al. [2] trains a neural network to learn feature vectors that describe 3D points in a scene. These learned features are then projected onto the target view and fed to a rendering network to produce the final novel image. Wiles et al. [51] lifts per-pixel features from a source image onto a 3D pointcloud that can be explicitly projected to the target view using a U-Net model. However, this method suffers from temporal instabilities between generated novel views of a smooth camera path. We propose to model the spatial-temporal relations between queried target poses to render a smooth sequence of novel views without per-scene optimization [37, 29].

The current state-of-the-art method Neural Radiance Fields (NeRF) by Mildenhall et al. [29] represents the plenoptic function by a multi-layer perceptron that can be queried using classical volume rendering to produce novel images. NeRF has to be evaluated at a large number of sample points along each camera ray. This makes rendering a full image with NeRF extremely slow. Despite the high quality of the synthesized novel images, NeRF also requires per-scene training. Recent volumetric approaches [55, 49, 50, 47] address the generalization issue of NeRF by incorporating a latent vector extracted from reference views. These methods show generalization on selected testing scenes, but they share the slow rendering property of NeRF [29]. We propose a novel adaptive depth scaling to produce up-to-scale depth maps on various types of 3D scenes. Thus, RGBD-Net achieves good performance on a testing set that is separate from the training set and completely new scenes outside those datasets. Since our method is fully convolutional, RGBD-Net also achieves faster rendering than NeRF and its variants.

3. Proposed method

This section describes in detail the architecture of RGBD-Net, which comprises of two modules: a hierarchical depth regression network $R$ (Section 3.1) that estimates the depth map of the novel view, and a depth-aware refinement network $G$ (Section 3.2) that enhances the warped images to produce the final target image. Last, we discuss the loss functions used to train the model in Section 3.3.

3.1. Depth regression network $R$

We first describe the pipeline (see Fig. 2) for estimating the depth map $D_q$ of the target view $s_q$ from a set of unstructured input images and their poses $\{I_n, s_n\}_{n=1,...,N}$. Each reference view $I_n$ is first fed to the Feature Pyramid Network [25] to extract $K$ multi-scale features $F^k_n$ [19]. We then apply homography warping to each feature map of $F^k_n$ to construct a PSV $P^k_n$ of the target view $s_q$ with a set of $M_k$ hypothesis depth planes. A mean PSV $P^k = \sum_{n=1}^{N} P^k_n / N$ is fed to a 3D U-Net to estimate a coarse novel depth map $\hat{D}^k_q$. Inspired by the recent work on multi-view stereo [52, 14], we estimate the depth map of the novel views in a coarse-to-fine manner. We first utilize the depth plane resampling technique from the MVS literature to efficiently sample $M_{k+1}$ depth planes using the predicted coarse novel depth map $\hat{D}^k_q$.

**Depth plane resampling.** The depth planes $d^1_i$ at the scale $k = 1$ are sampled from the initial depth range as follows:

$$d^1_i = d^\text{min} + i \Delta_1, \quad i = 1, ..., M_1$$

where $d^\text{min}$ and $\Delta_1$ are the minimum depth value and depth interval, respectively. At the later stages ($k > 1$), the adjusted depth ranges per pixel are selected such that, their centers lie at the estimated depth values obtained from the depth map of the previous stage. We then rewrite equation (1) to define the sampled depth plane $d^k_i(p)$ for a pixel $p$ as follows:

$$d^k_i(p) = d^\text{min}(p) + i \Delta_k, \quad i = 1, ..., M_k$$

$$d^\text{min}_i(p) = \hat{D}^{k-1}_q(p) - \frac{M_k \Delta_k}{2}$$

where $\hat{D}^{k-1}_q(p)$ is the predicted depth value of the pixel $p$ from the last stage. Instead of having a constant minimum depth value $d^\text{min}$, we leverage $\hat{D}^{k-1}_q$ to obtain adaptive $d^\text{min}_i(p)$ for each pixel $p$. The adaptive $d^\text{min}_i(p)$ narrows the sampled depth ranges and allows RGBD-Net to produce more accurate depth maps. The width and height of the PSVs are doubled when $k$ is increased by one (see Fig. 2). Therefore, we set $M_k = M_{k-1}/2$ and $\Delta_k = \Delta_{k-1}/2$ to narrow the depth range of the subsequent stage.

**Adaptive depth scaling** RGBD-Net focuses on solving the generalization problem of view synthesis. To address this
issue, we propose a scaling method to handle 3D scenes in various depth ranges. In practice, some depth ranges are from 0.1 to 1 or from 10 to 100. Note that, these numbers are not the absolute distances in some known units. Thus, we transform those depth ranges roughly to the same scale. Let \( d_{\text{min}} \) and \( d_{\text{max}} \) be the minimum and maximum depth values of an arbitrary 3D scene. We define a scaling factor \( f = C/d_{\text{min}} \) where \( C \) is a constant value. The minimum depth value of the depth plane resampling is then scaled so that \( d_{\text{min}} = C. \) Based on the per-scene scaling factor \( f, \) we can obtain the scaled depth interval \( \Delta_1 = (f d_{\text{max}} - C)/M_1. \) In all experiments, we use the same the number of hypothesis depth plane \( M_1 \) to save GPU memory.

If the ground-truth depth is available, we can train the \( R \) network with depth supervision. The ground-truth depth is scaled using the same scaling factor \( f. \) This method encourages depth robustness on various depth scales without per-scene optimization. If the ground-truth depth is not available, we use COLMAP [38] to perform sparse reconstruction and get the depth range of such testing scenes. We then scale the obtained depth range using the similar technique. The novel view evaluation in the Section 4 validates the generalization ability of RGBD-Net.

### 3.2. Depth-aware refinement network \( G \)

**Feature fusion.** We use differentiable bilinear interpolation from Jaderberg et al. [17] to map the learned features \( F^k_n \) of the Feature Pyramid Network to obtain the warped feature \( W^k_n \) using the previously regressed depth map. We then combine the set \( \{W^k_n\}_{n=1,...,N} \) to obtain the unified warped feature \( \hat{W}^k_q \) of the target pose \( s_q. \) We rely on the predicted depth map to calculate the 3D coordinates of every pixel \( p \) of the novel view. Using the known reference and target pose, we back-project that 3D point to the camera space of each reference view. The unified warped feature \( \hat{W}^k_q \) of the target pose is obtained as follows:

\[
\alpha^p_n = (1/z_n^p) / \sum_N 1/z_n^p \tag{4}
\]

\[
\hat{W}^k_q = \sum_N \alpha_n W^k_n \tag{5}
\]

where \( z_n^p \) and \( \alpha_n^p \) are the z-coordinate and the blending weight of the pixel \( p \) of the \( n^{th} \) reference view respectively. If the pixel \( p \) is not visible in all reference views then its weight is zero. We utilize the inverse of the z-coordinate to reduce the impact of far reference views from the target pose. Therefore, the blending weights \( \alpha_n \) rely on the predicted depth map to assign weights between reference views. As the depth network \( R \) gets better at predicting depth maps, so does the feature fusion method.

**Depth-aware synthesis network.** As illustrated in Fig. 3, the proposed depth-aware refinement network \( G \) predicts the novel view \( I_q \) of the target pose \( s_q \) using a set of \( K \) multi-scale features \( \{\hat{W}^k_q\}. \) We provide details of the 2D U-Net structure in the supplementary material.

To further enhance the overall quality of the predicted novel image, we leverage the complete predicted depth maps produced by the depth regression network \( R. \) Recent successes on conditional image synthesis [32, 59, 20] have shown that we can generate photo-realistic images conditioned on certain image data such as an image from another
Figure 3. We encourage a spatial-temporal consistency by training the depth-aware refinement network \( G \) to render \( Q \) nearby sampled novel views. Each novel view \( \hat{I}_q \) is predicted from a set a set of \( K \) multi-scale warped features \( \{ W^k_q \}_{k=1,...,K} \).

domain or a semantic segmentation map. We observe that the proposed \( R \) network produces depth maps with sharp edges. Therefore, we exploit this to guide the image synthesizing model to produce sharp novel images.

The predicted depth maps \( \hat{D}_q \) are fed to the Spatially-Adaptive Denormalization (SPADE) Resblocks \([32]\) to progressively predict the novel views in a coarse-to-fine manner. More specifically, each SPADE Resblock regularizes the decoder’s learned features based on the depth predictions. This transformation ensures that the predicted novel image has similar sharp edges as the depth map produced by the \( R \) network. Besides, utilizing the depth maps in the SPADE blocks provides a valid inductive bias to the refinement network for synthesizing the novel views even without explicitly learning the depth maps with ground truth.

**Spatial-temporal consistency.** RGBD-Net uses a set of sparse reference views to synthesize a novel view. Therefore, when generating videos along smooth camera paths, it is potentially subject to temporally inconsistent predictions and flickering artifacts due to the independent rendering at each new viewpoint.

To address the above issue, we include a ConvLSTM \([39]\) cell to model the spatial-temporal relations between \( Q \) randomly sampled novel views. Conventional LSTM utilizes the previous hidden state \( H_{q-1} \) to produce the current hidden state \( H_q \). In view synthesis, there are certain changes between viewpoints of the \( Q \) target views. Hence, we reflect these viewpoint changes by warping \([17]\) \( H_{q-1} \) using the previously predicted depth map \( \hat{D}_{q-1} \). The warped hidden state \( \hat{H}_{q-1} \) represents the encoded image feature of the previous novel view being warped to the current target pose \( s_q \). Let \( Q \) denote the output of the encoder, we obtain the novel view \( \hat{I}_q \) using ConvLSTM \([39]\) as follows:

\[
\hat{H}_{q-1} = \text{warping}(H_{q-1}, \hat{D}_{q-1}) \tag{6}
\]

\[
C_q, H_q = \text{ConvLSTM}(O_q, C_{q-1}, \hat{H}_{q-1}) \tag{7}
\]

\[
\hat{I}_q = \text{Dec}(H_q, S_q) \tag{8}
\]

where \( S_q \) is the skip connections from the encoder to the decoder. Instead of using the final output \( O_q \) of the encoder to render the novel view, we use the output hidden state \( H_q \) of the ConvLSTM as the decoder’s input to render the novel view \( \hat{I}_q \). As can be seen in (7), the learned ConvLSTM cell aggregates the current and prior encoded visual features of \( O_q \) and \( H_{q-1} \) to eliminate the temporal inconsistency between adjacent target poses.

### 3.3. Training

**Learning objective.** We trained the proposed method with an L1 image loss \( L_{I_1} \), perceptual loss \( L_p \) \([5]\) and hinge GAN loss \( L_G \) \([13]\) between the generated and ground-truth novel image. If the ground-truth depth map is available we can also use the scaled depth loss \( L_d \) \([15]\). The total loss is then \( L_{total} = \lambda_{I_1} L_{I_1} + \lambda_p L_p + \lambda_G L_G + \lambda_d L_d \). Note that our method does not strictly need the depth loss \( L_d \), which enables training on datasets that do not have ground-truth depth maps.

**Implementation details.** The models were trained with the Adam optimizer using a 0.004 learning rate for the discriminator, 0.001 for both the depth regression \( R \) and refinement generator \( G \) and momentum parameters (0, 0.9). \( \lambda_{I_1} = 1, \lambda_p = 10, \lambda_G = 1, \lambda_d = 1, K = 3, N = 7, C = 100, Q = 3, W = 640, H = 512 \). We implemented RGBDNet in PyTorch \([33]\), and training took 2-3 days on 4 Tesla V100 GPUs.

### 4. Experiments

**View selections.** We follow the view selection method of Riegler et al. \([36]\) to select the top 10 closest source images to each target image. During training, we randomly select \( N \) source images among the 10 closest views as inputs to our method. At each training step, we sample \( N \) uniformly at random from \([1, N]\). For each target pose, we randomly select \( Q - 1 \) nearby target poses. We train RGBD-Net to produce \( Q \) target poses in each forward pass to encourage the temporal consistency.

**Datasets.** We train RGBD-Net using the DTU \([1]\) and BlendedMVS \([53]\) datasets. DTU is an MVS dataset consisting of more than 100 scenes scanned in 7 different lighting conditions at 49 positions. From 49 camera poses, we selected 10 as targets for view synthesis and used the rest for source image selection. BlendedMVS \([53]\) is another large-scale MVS dataset which contains high quality rendered and real images with realistic ambient lighting.
Table 1. Quantitative comparison on large-scale dataset of synthetic and real images. For all datasets, the metrics (average over all target views) are reported. The RGBD-Net is trained with combined loss $L_{total}$, achieving best results without per-scene optimization. Performance without the depth loss $L_d$, denoted RGBD-Net*, is competitive. Methods with a † symbol are optimized per-scene. Finetuning scene-specific RGBD-Net† achieves state-of-the-art results on view synthesis.

| Method         | Tank&Temples [21] | DTU [1] | BlendedMVS [53] | Real Forward-Facing [28] |
|----------------|-------------------|---------|-----------------|------------------------|
|                | LPIPS↑ | SSIM↑ | PSNR↑ | LPIPS↑ | SSIM↑ | PSNR↑ | LPIPS↑ | SSIM↑ | PSNR↑ |
| pixelNeRF [55] | 0.65  | 0.496 | 12.25 | 0.54  | 0.857 | 19.25 | 0.48  | 0.724 | 16.28 |
| LLFF [28]      | 0.61  | 0.524 | 13.25 | 0.51  | 0.872 | 21.25 | 0.41  | 0.794 | 17.28 |
| FVS [36]       | 0.18  | 0.868 | 20.26 | 0.25  | 0.972 | 26.96 | 0.25  | 0.815 | 22.94 |
| RGBD-Net*      | 0.17  | 0.884 | 20.35 | 0.21  | 0.980 | 31.69 | 0.21  | 0.838 | 23.52 |
| RGBD-Net†      | 0.16  | 0.892 | 21.28 | 0.19  | 0.985 | 32.65 | 0.18  | 0.859 | 25.13 |
| RGBD-Net†      | 0.24  | 0.821 | 19.46 | 0.36  | 0.942 | 24.78 | 0.36  | 0.801 | 20.18 |
| NeRF++†        | 0.14  | 0.952 | 25.69 | 0.14  | 0.991 | 35.28 | 0.15  | 0.913 | 25.58 |
| RGBD-Net†      | 0.12  | 0.986 | 26.35 | 0.11  | 0.997 | 36.69 | 0.09  | 0.935 | 29.52 |
| RGBD-Net†      | 0.14  | 0.952 | 25.69 | 0.14  | 0.991 | 35.28 | 0.15  | 0.913 | 25.58 |
| RGBD-Net†      | 0.12  | 0.986 | 26.35 | 0.11  | 0.997 | 36.69 | 0.09  | 0.935 | 29.52 |
| RGBD-Net†      | 0.14  | 0.952 | 25.69 | 0.14  | 0.991 | 35.28 | 0.15  | 0.913 | 25.58 |

![Figure 4](https://example.com/fig4.png)

Figure 4. Exampled of generated novel views by RGBD-Net and state-of-the-art methods for three scenes from the Tanks and Temples (T&T) [21] dataset. We train RGBD-Net on the DTU [1] dataset and test it on T&T to evaluate the generalization ability.
Although this method has been trained on the train-set, it fails to capture thin structures (lamp post on Playground) and accurate boundary (ghosting artifacts in M60 and Truck), as seen in Fig. 4. FVS [36] struggles to recover clean and accurate novel views which do not require per-scene optimization. As can be performed by image-based rendering methods [28, 36, 55], the depth map at the target view to be perfectly accurate. We summarize the quantitative and qualitative results in Table 1 and Fig. 4. The model RGBD-Net*, which is trained without the ground truth depth loss $\mathcal{L}_d$, shows almost similar performance to the full model, while still being better than other baselines. We also observe no significant differences between the predicted novel views produced by RGBD-Net when trained with or without depth supervision. The goal of view synthesis is to produce faithful novel views and for that purpose, we do not strictly need the predicted depth map at the target view to be perfectly accurate.

We first evaluate RGBD-Net against the current top-performing image-based rendering methods [28, 36, 55] which do not require per-scene optimization. As can be seen in Fig. 4, FVS [36] struggles to recover clean and accurate boundary (ghosting artifacts in M60 and Truck), and fails to capture thin structures (lamp post on Playground). Although this method has been trained on the the training set of Tanks and Temples dataset [21], our base model RGBD-Net can render more realistic novel views compared to those produced by FVS [36]. We also test the generalization of RGBD-Net on the Real Forward-facing [28] dataset. LLFF [28] performs reasonably well on this dataset because the method is based on the MPI representation and assumes that camera poses lie on the same plane. The reference views of RGBD-Net does not need to follow that assumption. Experimental results show that our method performs substantially better than LLFF [28] on the real-world scenes.

PixelNeRF [55] is a recent approach to extend NeRF [29] for the generalization. Quantitative results show that this method does not perform well on the Tanks and Temples dataset [21]. To fairly evaluate the generalization ability of RGBD-Net against pixelNeRF [55], we evaluate them on the testing set of the DTU dataset [1]. In Fig. 5, we notice the lack of fine details in the novel views produced by pixelNeRF [55], which reflect the lower quantitative performance. Both RGBD-Net and pixelNeRF [55] use extracted features from reference images to render the novel view. However, we train RGBD-Net to produce coarse-to-fine features to predict both color and depth images of the novel views. In case of pixelNeRF [55], the single-scale feature maps are not optimized to condition their learned radiance field. Moreover, RGBD-Net generates the whole image significantly faster than those produced by pixelNeRF [55] due to the fully convolution architecture. Therefore, our method not only produce better novel views but also render them significantly faster than other baselines [29, 56, 55, 47, 49]. Comparisons on the average execution time of RGBD-Net and other methods are included in the supplementary material.

Finally, we compare RGBD-Net against recent view synthesis methods [2, 56] that require per-scene optimization. To compete fairly with these methods, we also fine-tune our pre-trained model on each scene and denote it as RGBD-Net†. After finetuning, RGBD-Net† achieves state-of-the-art results of view synthesis compared to baseline methods which are trained with or without per-scene optimization. In Fig. 4, NeRF++ [56] fails to render photorealistic novel views due to some unrealistic noises and blurry edges. A key component in NeRF [29] and its variants is the use of the positional encoding [44] which helps generate high frequency details, but positional encoding may also cause unwanted high-frequency artifacts in images, which reduces perceptual quality.

5. Ablation study

Architecture design. Table 2 and Fig. 6 summarizes the quantitative and qualitative results on different architecture choices using the test set of the Tanks and Temples dataset [21]. RGBD-Net without the proposed adaptive depth scal-
Figure 6. Comparison of the ground-truth with predicted novel views by RGBD-Net without the proposed adaptive depth scaling (ADS), without SPADE Resblocks and the full model.

|                   | LPIPS↓ | SSIM↑ | PSNR↑ |
|-------------------|--------|-------|-------|
| No adaptive depth scaling | 0.38   | 0.752 | 18.52 |
| No SPADE Resblocks   | 0.26   | 0.815 | 19.17 |
| No spatial-temporal consistency | 0.21   | 0.879 | 19.94 |
| RGBD-Net (full)        | **0.16** | **0.892** | **21.28** |

Table 2. RGBD-Net architecture ablation study. Reconstruction accuracy of novel view synthesis on the Tanks and Temples dataset [21].

| # of reference images | LPIPS↓ | SSIM↑ | PSNR↑ |
|----------------------|--------|-------|-------|
| 4                    | 0.267  | 0.796 | 0.802 |
| 5                    | 0.203  | 0.825 | 0.871 |
| 6                    | 0.185  | 0.871 | 0.890 |
| 7                    | **0.160** | **0.890** | **0.890** |
| 8                    | 0.168  | 0.871 | 0.890 |
| 9                    | 0.171  | 0.871 | 0.890 |
| 10                   | 0.175  | 0.871 | 0.887 |

Table 3. The impact of the number of reference images, measured in terms of novel view reconstruction accuracy on the Tank and Temples dataset [21].

Visualizing generated depths. In Fig. 7, we show qualitative results on the predicted depth map of the reference camera compared to those produced by the current top-performing MVS method [14]. Learning-based MVS methods [52, 14] are trained to predict only depth maps of the given target image and its nearby views. Using the same set of unstructured inputs, RGBD-Net is trying to solve a more challenging problem of predicting both the depth and the color images of the target pose. We observe that our method is able to generate an accurate depth map of the target view without using the reference image as input. Moreover, we also show that our method performs well on unseen data. In Fig. 1 and Fig. 4, our proposed method is able to predict both the depth maps and the color images of the target views and then use them to reconstruct a 3D point cloud on the Tanks and Temples [21] dataset.

6. Conclusions

We presented RGBD-Net, a new method to address the challenging problem of novel view synthesis from a sparse and unstructured set of input images. Due to its adaptive depth scaling and depth-aware generator network, RGBD-Net is able to produce high-quality depth maps and color

![Figure 7. Examples of estimated depth maps using RGBD-Net and CasMVSNet [14] on the DTU [1] dataset.](image-url)
images of the target views without per-scene optimization. RGBD-Net also achieves unprecedented levels of realism in free-viewpoint video thanks to its novel spatial-temporal module that allows smooth rendering of continuous camera motion.

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Appendix of RGBD-Net

\[
\{I_n, s_n\}_{n=1}^{N} \xrightarrow{s_q} \{R \rightarrow \hat{D}_q \rightarrow G \rightarrow \hat{I}_q\} \rightarrow \hat{D}_n
\]

Figure 8. The illustration of how RGBD-Net produces the RGB image \( \hat{I}_q \), depth map \( \hat{D}_q \) at the target view \( s_q \) and the depth map \( \hat{D}_n \) of the reference pose \( s_n \) in the testing time. Blue arrow indicates the input pose of the depth regression network \( R \).

A. Multi-view stereo evaluation

Pointcloud generation. Similar to previous works [52, 14] on MVS, we apply depth map filter and fusion approach [12] to merge all predicted novel views and depth maps into a unified pointcloud output. In the testing time, we predict the depth map \( \hat{D}_n \) of each reference view \( I_n \) using the trained depth regression network \( R \) as can be seen in Fig. 8. We use the union set \( \Psi = \{\hat{I}_q, \hat{D}_q\}_{q=1}^{Q} \cup \{I_n, \hat{D}_n\}_{n=1}^{N} \) of the estimated novel views and depth maps as inputs for pointcloud generation.\(^1\) We apply two-step depth map filtering strategy to remove outliers. Finally, median depth map fusion is applied to refine all depth maps. The 3D pointcloud is obtained by projecting all refined depth maps into the 3D space.

Baselines. We evaluate the predicted depth maps produced by RGBD-Net against MVS methods [52, 6, 54, 8, 14] on the DTU [1] test set and the intermediate set of Tanks and Temples [21] dataset. We use fusible [12] as the post-processing step to reconstruct the 3D point cloud of the scene. Therefore, a more accurate and consistently estimated depth map would lead to better performance in 3D reconstruction. We note that our problem is a more challenging case since RGBD-Net predicts both the target depth maps and color images using only the reference views. Whereas, all other MVS methods predict only the depth maps at the reference poses while using the reference images as input.

Metrics. We calculate the mean accuracy, completeness and overall using the evaluation code provided by [1]. The average of mean accuracy and completeness represent the reconstruction quality. Moreover, we also calculate the mean F-score on the Tanks and Temples [21] dataset.

Results. As can be seen in Table 4, the proposed method trained without the depth loss (RGBD-Net\(^*\)) shows competitive performance with other MVS baselines. Using the ground-truth depth loss, our full model (RGBD-Net) achieves the best mean F-score on Tanks and Temples and the best overall distance on DTU. We observe that our method is able to generate accurate depth map of the target view without using the reference image as input. Moreover, we also show that our method performs well on unseen data. Fig. 10, 11 and 12 show more examples of generated pointclouds using the proposed RGBD-Net on the Tanks and Temples [21], DTU [1] and BlendedMVS [53] datasets, respectively.

B. Spatial-temporal consistency

We found that optimizing RGBD-Net to produce a smooth sequence of novel views significantly enhances the overall quality of the independent rendering as can be seen in the Table 2 of the main paper. Thus, we provide qualitative results of a sequence of novel views produces by RGBD-Net with and without the proposed spatial-temporal consistency module. As can be seen in Fig. 9, the predicted novel views include significant artifacts near the boundary and also not very temporally consistent due to independent renderings at each novel viewpoint using 2D/3D U-Net. The proposed depth-aware ConvLSTM allows RGBD-Net to retain the hidden state from previous steps and refine the current generated novel view.

C. Execution time

In Table 5, we report the average execution times to synthesize a novel image between RGBD-Net with different methods. In all experiments, we synthesize the novel image with the size of 640 × 512 pixels using 4 reference views on the T&T datasets. Notice that, RGBD-Net is 52 times faster than the current state-of-the-art neural rendering method NeRF++ [56]. Moreover, our method also runs faster than other image-based rendering techniques while maintaining superior performance.

D. Implementation details

Training. We trained RGBD-Net on the DTU dataset for 25 epochs and subsequently finetuned it on the BlendedMVS dataset for 30 epochs. The models were trained with the Adam optimizer with a batch size of 4. In both training sets, the input and output reference views have the same image size of 640 × 512 pixels and we set the number of reference views to \( N = 4 \). To balance between accuracy and efficiency, we adopt a three-scale (\( K = 3 \)) depth regression network \( R \). Accordingly, the spatial resolution of extracted feature maps \( F_n^k \) is set to 1/16, 1/4 and 1 of the original image size.

Adaptive depth scaling. In Section 3.1 of the paper, our

\(^1\)We use the predictions of the final scale so superscript \( k \) is omitted.
Table 4. Point cloud accuracy on the DTU test [1] and Tanks and Temples [21] intermediate datasets.

| Methods            | Acc.↓ (mm) | Comp.↓ (mm) | Overall↓ (mm) | Mean↑ | Francis↑ | Horse↑ | Lighthouse↑ | M60↑ | Panther↑ | Playground↑ | Train↑ |
|--------------------|------------|-------------|---------------|-------|----------|--------|-------------|------|----------|-------------|-------|
| MVSNet [52]        | 0.456      | 0.646       | 0.551         | 43.48 | 55.99    | 28.55  | 25.07       | 50.79| 53.96    | 50.86       | 47.90 |
| Point-MVSNet [6]   | 0.361      | 0.421       | 0.391         | 48.27 | 61.79    | 41.15  | 34.20       | 50.79| 51.97    | 50.85       | 52.38 |
| PVA-MVSNet [54]    | 0.352      | 0.414       | 0.383         | 54.46 | 69.36    | 46.80  | 46.01       | 55.74| 57.23    | 54.75       | 56.70 |
| UCSNet [8]         | 0.330      | 0.392       | 0.361         | 54.83 | 76.09    | 53.16  | 43.04       | 54.00| 55.81    | 52.78       | 57.38 |
| CasMVSNet [14]     | 0.325      | 0.385       | 0.355         | 56.84 | 76.37    | 58.45  | 58.26       | 55.02| 55.81    | 58.18       | 47.89 |
| RGBD-Net           | 0.334      | 0.390       | 0.349         | 59.32 | 77.01    | 60.25  | 47.09       | 63.45| 62.19    | 55.16       | 59.27 |
| RGBD-Net (w/o ConvLSTM) | 0.334 | 0.390 | 0.349 | 59.32 | 77.01 | 60.25 | 47.09 | 63.45 | 62.19 | 55.16 | 59.27 |
| RGBD-Net (full)    | 0.320      | 0.381       | 0.349         | 59.32 | 77.01    | 60.25  | 47.09       | 63.45| 62.19    | 55.16       | 59.27 |

Table 5. Comparisons on the average execution time of RGBD-Net and other view synthesis methods.

| Methods        | pixNeRF [55] | LLFF [28] | FVS [36] | NPBG [2] | NeRF++ [56] | RGBD-Net (ours) |
|----------------|--------------|-----------|----------|----------|-------------|-----------------|
| Avg time (ms / img) | 9262 | 651 | 541 | 352 | 8153 | 156 |

E. Additional qualitative results

In this section, we provide additional qualitative results. Fig. 13, 14 and 15 show more examples of rendered novel views using RGBD-Net and other view synthesis methods on the Tanks and Temples [21], DTU [1] and BlendedMVS [53] datasets, respectively. For NeRF [29], we manually define the bounding volume around the main object in each testing scene.

**Depth map regression.** Inspired by current learning-based MVS methods [52, 14], the predicted depth map is regressed from the probability volume via the $soft-argmax$ operation. We denote the probability volume over all the $M_k$ depth hypothesis as $V^k$. The predicted depth value $\hat{D}_q^k(p)$ of each pixel $p$ is defined as follows:

$$\hat{D}_q^k(p) = \sum_{i=1}^{M_k} d_{ki}^V(p)$$

**Figure 9.** A generated sequence $\{\hat{I}_q\}$ of novel views produced by RGBD-Net with and without the spatial-temporal consistency module.
Figure 10. Pointcloud results of RGBD-Net on the *intermediate set* of Tanks and Temples [53] dataset.
Figure 11. Pointcloud results of RGBD-Net on the DTU test set [1].
Figure 12. Pointcloud results of RGBD-Net on the BlendedMVS test set [53].
Figure 13. Additional qualitative results on Tanks and Temples dataset [21]. RGBD-Net * is our proposed RGBD-Net trained without the ground-truth depth loss. We observe no significant difference on the performance of view synthesis between RGBD-Net and RGBD-Net *.
Figure 14. Additional qualitative results on DTU dataset [1].
Figure 15. Additional qualitative results on BlendedMVS dataset [53].