Geo-NI: Geometry-aware Neural Interpolation for Light Field Rendering

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Abstract—In this paper, we present a Geometry-aware Neural Interpolation (Geo-NI) framework for light field rendering. Previous learning-based approaches either rely on the capability of neural networks to perform direct interpolation, which we dubbed Neural Interpolation (NI), or explore scene geometry for novel view synthesis, also known as Depth Image-Based Rendering (DIBR). Instead, we incorporate the ideas behind these two kinds of approaches by launching the NI with a novel DIBR pipeline. Specifically, the proposed Geo-NI first performs NI using input light field sheared by a set of depth hypotheses. Then the DIBR is implemented by assigning the sheared light fields with a novel reconstruction cost volume according to the reconstruction quality under different depth hypotheses. The reconstruction cost is interpreted as a blending weight to render the final output light field by blending the reconstructed light fields along the dimension of depth hypothesis. By combining the superiorities of NI and DIBR, the proposed Geo-NI is able to render views with large disparity with the help of scene geometry while also reconstruct non-Lambertian effect when depth is prone to be ambiguous. Extensive experiments on various datasets demonstrate the superior performance of the proposed geometry-aware light field rendering framework.

Index Terms—Light field rendering, view synthesis, depth estimation, deep learning.

I. INTRODUCTION

LIGHT field (LF) describes rays travelling from all directions in a free space [1], demultiplexing the angular information lost in conventional 2D imaging. Benefits from the LF rendering technologies [1], [2], LF enables to reproduce photorealistic views in real-time, enabling travelling freely in metaverse. Standard LF rendering technologies require a Nyquist rate view sampling, i.e., densely-sampled LF with disparities between adjacent views to be less than one pixel [3]. However, existing densely-sampled LF devices or systems [4] either suffers from a long period of acquisition time or falls into the well-known resolution trade-off problem, i.e., sacrificing the spatial resolution for a dense sampling in the angular domain.

With the success of deep learning in artificial intelligence [5], recent researches [6], [7], [8], [9] are stepping towards deep learning-based interpolation, which we refer to as Neural Interpolation (NI), or Depth Image-Based Rendering (DIBR) using a sparsely-sampled LF in the angular domain. On the one hand, typical learning-based NI methods [10], [7], [11] directly map the low angular resolution LF to densely-sampled LF through diverse network architectures. These methods are highly effective in modelling non-Lambertian effects. Nevertheless, the perception range (receptive filed) of the network [12], [13] limits the performance on LF with large disparities, leading to aliasing effects in the reconstructed LF. On the other hand, state-of-the-art learning-based DIBR methods [6], [9], [14] resort to depth estimation followed by view synthesis, which is considered to be a more efficient way to deal with the large disparity issue than only relying on the receptive filed. But these methods require depth consistency along the angular dimension, and thus, often fail to handle the depth ambiguity caused by the non-Lambertian effect.

In this paper, we propose a learning-based framework for geometry-aware LF rendering to address the non-Lambertian and large disparity issues by launching the NI within a novel DIBR pipeline. We term the framework as Geo-NI, as shown in Fig. 1. Specifically, we bridge the gap between the standard NI and DIBR by shearing the input LF with a set of depth hypotheses. The NI part is achieved via a neural network that directly interpolates the sheared LFs. Then the DIBR part is implemented via another neural network to assess the reconstruction quality of the neural interpolated LFs under the depth hypotheses. The DIBR part constructs a cost volume, where each value in the volume can be interpreted as a weight for blending the final rendered (output) LF, as shown in Fig. 1. We therefore name the volume reconstruction cost volume. By incorporating the two parts, the proposed Geo-NI framework is able to synthesize views with large disparity while also reconstruct non-Lambertian effect when depth is prone to be ambiguous.

To efficiently extract high-level LF feature in the NI and DIBR parts, we propose a hierarchical packing-unpacking structure that is able to encode and decode the LF features. The building block of the packing/unpacking structure is spatial-to-channel/channel-to-spatial pixel shuffling followed
Fig. 1. We present Geo-NI framework for geometry-aware light field rendering by launching the Neural Interpolation (NI) within a novel Depth Image-Based Rendering (DIBR) pipeline. The proposed framework is able to render LFs with large disparity while also reconstruct the non-Lambertian effects. LF courtesy of Adhikarla et al. [15].

by convolional layers. With the help of the spatial-channel pixel shuffling, the networks in Geo-NI are able to efficiently gain a large perceptive field by intactly compressing the spatial resolution and restore it without losing high frequencies. In summary, we make the following contributions:

- A Geometry-aware Neural Interpolation (Geo-NI) framework that joints neural interpolation and depth-based view synthesis for solving non-Lambertian and large disparity challenges in an end-to-end manner;
- A novel reconstruction cost volume derived from the DIBR pipeline that guides the blending of the LFs sheared by different depth hypotheses as well as the rendering of scene depth, as shown in Fig. 1;
- A hierarchical packing-unpacking structure that efficiently encodes and decodes the LF features via spatial-channel pixel shuffling.

We demonstrate the superiority of the proposed Geo-NI framework by performing extensive evaluations on various LF datasets. The proposed network presents high-quality DSLF on challenging cases with both non-Lambertian effects and large disparities.

II. RELATED WORK

A. Plenoptic Sampling and Reconstruction

These approaches treat LF reconstruction as the approximation of plenoptic function using a set of samples. The analysis tools in the Fourier domain show that the sampling produces spectrum replicas along the sample dimensions. Under sparse sampling, the replicas will overlap with its original spectrum, resulting aliasing effects in the LF signals. Classical approaches by Chai et al. [16] and Zhang et al. [17] formulate the reconstruction as filtering of the aliasing high-frequencies while keeping the original spectrum as completely as possible. In [18], Vagharshakyan et al. explored a shearlet transform of composite directions and scales in the Fourier domain to remove the aliasing high-frequencies. To handle the occlusion problem, Zhu et al. [19] proposed an occlusion field theory to quantify the occlusion degree, and designed a reconstruction filter to compensate the missing information caused by the occlusion.

Researchers also focus on training a deep neural network to directly infer the densely-sampled LF from the low angular resolution input [10], [7], [11], [20]. We term this kind of approaches as Neural Interpolation (NI) since they regard the reconstruction as a learning-based interpolation problem of the missing pixels (samples) without exploiting scene geometry. An initial work by Yoon et al. [10] first interpolates the low angular resolution LF with bicubic operation, then employs a convolutional network to refine the reconstructed LF. For explicitly handling the aliasing effects, Wu et al. [7] proposed a “blur-restoration-deblur” framework that first suppresses the high frequency components in the spatial dimension and then restores them via a non-blind deconvolution. Wang et al. [21] applied 3D convolution layers to reconstruct the two angular dimensions of the input LF sequentially. However, the small perception range, i.e., receptive filed [12], [13], impedes the networks to capture long-term correspondences in the input LF, resulting limited performances.

Recent works resort to a deeper network or an efficient architectures to enlarge the receptive field. Yeung et al. [11] directly fed the entire 4D LF into a pseudo 4D convolutional network, and proposed a novel spatial-angular alternating convolution to iteratively refine the angular dimensions of the LF. Jin et al. [14] further extended the spatial-angular alternating convolution to the problem of compressive LF reconstruction. Zhu et al. [20] introduced a U-net architecture to enlarge the receptive field using strided convolutional layers and convLSTM layers [23]. Liu et al. [24], Zhang et al. [25] and Meng et al. [26] applied residual blocks [27] and dense blocks [28] to prevent gradient vanishment when increasing the depth of the networks. Ying et al. [22] proposed a LF disentanglicing mechanism to disentangle the coupled spatial-angular information by using dilated and strided convolutions directly on the macro-pixel image. However, since the actual size of the receptive field can be smaller than its theoretical size [13], simply pursuing a deeper network without modeling the scene geometry still limits the performance of NI-based approaches.

B. Depth Image-based Rendering

These approaches first estimate the scene geometry (or depth), then warp the input images to the target viewpoint according to the estimated geometry and blend them. Standard LF depth estimation approaches follow the pipeline of stereo matching [29], which consists of feature description (extraction), cost computation, cost aggregation (or cost volume filtering), depth regression and post refnement. Because the difference of the data attribute, LF provides various depth cues for the feature description and cost computation, e.g., structure tensor-based local direction estimation [30], orthographic Hough transform for curve estimation [31], depth from correspondence [32], depth from defocus [33], [34] and depth from parallelogram cues [35]. Some recent learning-based approaches also explored the cost aggregation and depth regression in the aforementioned pipeline with 2D or 3D convolution networks [36], [37].

For rendering or synthesizing a novel view, typical DIBR approaches first warp the input views to the novel viewpoint
with sub-pixel accuracy and then blend them using different strategy, such as total variation optimization \cite{30}, soft blending \cite{33} and learning-based synthesis \cite{39, 40, 41}. The most representative DIBR approaches \cite{42, 46} using deep learning techniques employ a sequential network setting, and train the network models by minimizing errors between the synthesized views and the desired outputs (labels). An initial work by Kalantari et al. \cite{0} proposed an end-to-end DIBR framework using two sequential networks to infer depth and color, respectively. Following this setting, Shi et al. \cite{43} proposed to render novel views by blending the warped images in both pixel-level and feature-level. Meng et al. \cite{44} introduced a network for estimating warping confidences that address the errors around occlusion regions. Jin et al. proposed a spatial-angular alternating refinement network for images warped by using a regular sampling pattern (four corner views) \cite{45} and a flexible sampling pattern \cite{46}.

Different from the sequential network settings, recent researches \cite{47, 48} focus on decomposing input RGB images into depth-dependent layers, which is dubbed Multi-Plane Image (MPI). For example, Zhou et al. \cite{47} proposed a learning-based framework that infers a single MPI and a background image from two stereo images and synthesizes novel views via alpha blending. Based on this pioneer work, Mildenhall et al. \cite{9} proposed to infer an MPI for each view in the input LF and synthesize novel views by blending the local MPFs.

The aforementioned DIBR approaches directly blending the views warped according to the depth map or depth-related layers, which is highly effective for scenes with large disparity. However, since the depth information is deduced based on the Lambertian assumption, it will appear ambiguity around non-Lambertian regions, resulting in ghosting effects in the synthesized views. In this paper, instead of directly performing pixel or layer-wise warping using depth information, we propose to render the entire high-angular resolution LF by blending the neural interpolated LFs. Due to the NI does not rely on depth information, the proposed Geo-NI framework shows higher reconstruction quality around non-Lambertian regions.

### III. METHODOLOGY

A LF can be parameterized as a 4D function using two-plane representation \cite{1}, i.e., \( L(x, y, s, t) \in \mathbb{R}^{W \times H \times A_x \times A_t} \), with \((x, y)\) denoting the spatial plane and \((s, t)\) the angular plane. A sub-aperture image is obtained by fixing two angular dimensions of the 4D LF \( I(x, y) = L_{x,y}(x, y) \). An Epipolar Plane Image (EPI) is extracted by fixing one spatial dimension and one angular dimension, \( E(x, s) = L_{x,s}(x, s) \) or \( E(y, t) = L_{y,t}(y, t) \). In this paper, we use 3D LF slice with two spatial dimensions and one angular dimension, i.e., \( L(x, y, s) = L_{x,y}(x, y, s) \) or \( L(x, y, t) = L_{x,t}(x, y, t) \). By splitting LFs into 3D slices, the proposed method can be applied to both 3D LFs from a single-degree-of-freedom gantry system \cite{15, 49} and 4D LFs from plenoptic camera \cite{50} or camera array system. For the reconstruction of a 4D LF \( L(x, y, s, t) \), we employ a hierarchical reconstruction strategy introduced in \cite{7}. In the first step, we first reconstruct 3D LFs using slices \( L_{x,y}(x, y, s) \) and \( L_{y,t}(x, y, t) \) as input. We then apply the previously reconstructed 3D slices to synthesize the final 4D LF.

In this section, we first introduce the Geometry-aware Neural Interpolation (Geo-NI) framework in Sec. III-A, then discuss the relation between the Geo-NI and standard DIBR pipeline in Sec. III-B, and finally present the proposed hierarchical packing-unpacking structure in details (Sec. III-B).

#### A. Geometry-aware Neural Interpolation Framework

In this paper, we hope to design a geometry-aware LF rendering framework that promises to solve the non-Lambertian and large disparity issues in an end-to-end manner. Our proposal is to solve these issues by implanting the characteristic of NI into a DIBR pipeline. The overall framework is depicted in Fig. 2. In the following, we will explain the details of the proposed framework according to the order of the dataflow.

**Shearing operation.** It is an essential module that bridges the NI part and the DIBR part in the proposed framework. The shearing operation directly alters disparity by shifting all the sub-aperture images synchronously \cite{51, 33}. For an input 3D LF slice \( L(x, y, s) \) (or \( L(y, x, t) \)), we first shear it with a set of depth hypotheses \( d \in D \). The shearing operation can be formulated as follows

\[
\mathcal{H}_d(L(x, y, s)) = L(x + \left(s - \frac{S}{2}\right) \cdot d, y, s),
\]

where \( \mathcal{H}_d(\cdot) \) denotes the shearing operation with depth hypothesis \( d \) and \( S \) is the angular resolution of the input LF slice. The vanilla implementation in \cite{51, 33} describes the shearing operation as \( \tilde{L}(x + s \cdot d, y, s) \). We add the term \(-\frac{S}{2} \cdot d\) to avoid losing too many boundary pixels in the spatial dimension \( x \).

Besides, in our implementation we use zero padding for the blank regions caused by the shearing operation.

**Neural interpolation.** The shearing operation generates \( D \) sheared LF slices \( \mathcal{H}_{d=\ldots,D}(L(x, y, s)) \) as indicated in Fig. 2(a). We then feed the slices into a neural network, which we dubbed NI network, to directly reconstruct them into high angular resolution LFs. This step can be denoted as

\[
\tilde{L}_d(x, y, s) = f_N(\mathcal{H}_d(L(x, y, s)); \theta),
\]

where \( f_N(\cdot; \theta) \) is the NI network with trainable parameters \( \theta \).

**Detailed configuration of the NI network will be introduced in Sec. III-B.**

Note that the reconstructed LFs after this step are still under the deformation effect of the shearing operation. Therefore, we apply another shearing operation to eliminate this effect after the plenoptic reconstruction, which is termed as inverse shearing for short. This step can be denoted as

\[
\tilde{L}_d(x, y, s) = \mathcal{H}_{-\alpha}(\tilde{L}_d(x, y, s)),
\]

where \( \alpha \) is the upsampling factor in the angular dimension and \( \mathcal{H} \) is the shearing operation described in Eqn. 1. Due to the reconstruction, the shear amount in the inverse shearing operation is \(-\frac{d}{\alpha} \) rather than \(-d \).

**Reconstruction cost volume.** In this step, we define the aliasing in reconstructed LF as a kind of cost, which is similar with the matching cost in typical depth estimation
or DIBR. We term the cost as reconstruction cost. After the reconstruction and the inverse shearing, we feed the slices \(\tilde{L}_{d,\text{D}}(x, y, s)\) into another neural network, which is termed as DIBR network, as shown in Fig. 2(b). The DIBR network outputs a reconstruction cost volume \(C_{d,\text{D}}(x, y, s)\) that indicates the aliasing degree of the reconstructed LFs. This step can be described as
\[
C_d(x, y, s) = f_D(\tilde{L}_d(x, y, s); \vartheta), \; d \in D,
\]
where \(f_D(\cdot; \vartheta)\) denotes the DIBR network with trainable parameters \(\vartheta\). Detailed configuration of the DIBR network will be introduced in Sec. III-B. Despite the objective of the proposed Geo-NI is LF reconstruction, we can conveniently render a depth map from the DIBR network. Please refer to Sec. V-A for detail.

**Blending.** The final rendered high-angular resolution LF \(\hat{L}(x, y, s)\) is obtained by blending the reconstructed LFs sheared by all the depth hypotheses \(\tilde{L}_{d,\text{D}}(x, y, s)\). In this perspective, the reconstruction cost volume \(C_{d,\text{D}}(x, y, s)\) is considered as weight maps. While directly weighting each reconstructed LF \(\tilde{L}_d\) by reconstruction cost \(C_d\) will cause numerical instability. We therefore use normalized cost to formulate the blending
\[
\hat{L}(x, y, s) = \sum_d \tilde{L}_d(x, y, s) \odot \sigma_d(-C_d(x, y, s)),
\]
\[
\sigma_d(-C_d(x, y, s)) = \frac{\exp(-C_d(x, y, s))}{\sum_{d'} \exp(-C_{d'}(x, y, s))},
\]
where \(\odot\) is the Hadamard product, i.e., element-wise multiplication and \(\sigma_d\) is the softmax function. It should be noted that a smaller reconstruction cost indicates less degree of aliasing effect in the reconstructed LF, i.e., a higher reconstruction quality. We therefore normalize the reconstruction cost volume \(C_{d,\text{D}}(x, y, s)\) using softmax nonlinearity in Eqn. 2.

### B. Packing-Unpacking Network

Typical learning-based reconstruction methods \cite{52, 47, 9, 53} pursue a larger size of receptive field through spatial downsampling to achieve a higher reconstruction quality, e.g., strided convolutions, max-pooling and average-pooling. However, recent researches \cite{54, 55, 56} show that the commonly used downsampling methods ignore the sampling theorem, leading to performance degradation for tasks requiring fine-grained details. In comparison, we propose a novel hierarchical packing-unpacking structure that is able to efficiently increasing the receptive field while also preserving high frequency details for LF reconstruction, as shown in Fig. 3(a). In the following, we first introduce the proposed packing-unpacking structure, and then present the NI and DIBR networks constructed based on the structure.

1) **Hierarchical packing-unpacking structure:** In a packing block, we encode high spatial resolution LF (features) into high-level features by using a Spatial-to-Channel Pixel Shuffling (S2C-PS) \cite{57} followed by a residual module \cite{27} of two convolutional layers, as shown in the left part of Fig. 3(b). Analogously, in an unpacking block we replace the S2C-PS with its reverse operation, Channel-to-Spatial Pixel Shuffling (C2S-PS), to achieve the decode, as shown in the right part of Fig. 3(b). Different with the vanilla version in \cite{57}, we only fold one spatial dimension of feature maps into extra feature channels since the depth information is mainly weaved in one spatial dimension on the epipolar plane, as shown in Fig. 3(c). For example, the 5D feature tensor \(\phi \in \mathbb{R}^{B \times W \times H \times A \times C}\) is converted to \(\phi' \in \mathbb{R}^{B \times W \times 2 \times H \times A \times 2C}\) using the S2C-PS operation.

By stacking the blocks symmetrically, we then construct a hierarchical packing-unpacking structure that reduces the spatial resolution of the input LF in the bottleneck. Since the S2C-PS and S2C-PS are two reversible operations, the proposed packing-unpacking structure is able to gain a large receptive field without high frequency loss.

2) **Network architectures:** The networks in our proposed framework can be split into three parts: an encoder that extract high-level but low resolution features from high (spatial) resolution input, a bottleneck that performs non-linear mapping, and a decoder that restore high resolution target, i.e., a LF or a slice of the reconstruction cost volume, from high-level low resolution features. Table I lists the detail configurations of the
The inputs of the networks are 6 dimensional tensors of shape $D \times B \times W \times H \times A \times C$ (i.e., shear, batch, width, height, angular and channel). A straightforward implementation is to employ a network that is fully convolutional along the shear, width, height and angular dimensions. However, this architecture design will make the network parameters extremely large due to the requirement of 4D convolution. Fortunately, each slice $H_d(L)$ in the reconstruction task (NI network) or $\hat{L}_d$ in the cost assignment task (DIBR network) is independent along the shear dimension. Therefore, we can feed them to the networks slice by slice, i.e., $H_d(L)$ or $\hat{L}_d$. In our practice implementation, we employ a more efficient implementation by reshaping the network inputs into 5 dimensional tensors of shape $DB \times W \times H \times A \times C$. Then the reconstructed slices or the reconstruction cost volume can be inferred with a single forward-propagation.

### C. Implementation

1) Training objective: In a narrow sense, the objectives between the NI and DIBR networks in our framework is different. The objective of the NI network is to reconstruct a high angular resolution LF. While the objective of the DIBR network is to evaluate whether the LF is well reconstructed under a certain depth hypothesis. The latter objective is hard to achieve when the ground truth depth is unavailable. Fortunately, from a macro perspective, the objective of the entire framework is to synthesize a high-quality LF. In addition, all modules in our framework are differentiable, and thus, the proposed Geo-NI framework can be trained in an end-to-end manner.

We measure the $L_1$ distance between the reconstructed light filed $\hat{L}$ and the desired high angular resolution LF $L$ to optimize the parameters $\theta$ in the NI network, and the $L_1$ distance between the final output $\hat{L}$ and the desired LF $L$ to optimize the parameters $\theta$ in the DIBR network. The overall training objective is formulated as follows

$$\min_{\theta, \vartheta} \sum_n ||\hat{L}_{d}^{(n)} - L^{(n)}||_1 + ||\hat{L}^{(n)} \odot M - L^{(n)} \odot M||_1,$$

where $\hat{L}_{d}$ indicates the LF with shear amount $d = 0$, $n$ denotes the $n$th training instance, $M$ is a binary mask that avoids computing the loss on pixels that do not have valid values caused by the shearing operation and $\odot$ denotes element-wise multiplication.

2) Training Data: We train the networks in the proposed Geo-NI framework by using LFs from the Stanford (New) Light Field Archive [59], which contains 12 LFs with $17 \times 17$
views (the Lego Gantry Self Portrait is excluded due to the moving object in the scene). Since the network input is 3D LFs, we can extract 17 \( L(x, y, s) \) and 17 \( L(y, x, t) \) in each 4D LF set. To enhance the performance of the DIBR network, we augment the extracted 3D LFs using the shearing operation in Eqn. 1 with shear amounts \( d = \pm 2 \). This augmentation increases the number of training examples by 2 times. In the training procedure, we crop the extracted 3D LFs into sub-LFs with spatial resolution 128 \( \times \) 18 (width and height) and a stride of 40 pixels. We have three settings with respect to the reconstruction factors \( \alpha = 4, 7 \) in the NI network. Thus, the input/output angular resolution of the training samples for the Geo-NI framework are 5/17 and 3/15, respectively. Although the reconstruction factor of the network is fixed, we can achieve a flexible upsampling rate through network cascade.

3) Training Details: In our implementation, the reconstruction is performed on the luminance channel (Y channel) in the YCbCr color space. The parameters in the networks are initialized with values drawn from the normal distribution (zero mean and standard deviation of \( 1 \times 10^{-2} \)). We optimize the networks by using ADAM solver \([60]\) with learning rate of \( 1 \times 10^{-4} \) (\( \beta_1 = 0.9, \beta_2 = 0.999 \)) and mini-batch size of 8. The network converges after 200 epochs on the training dataset. The proposed Geo-NI is implemented in the Pytorch framework \([61]\).

IV. EVALUATIONS

In this section, we evaluate the proposed Geo-NI framework on various kinds of LFs, including those from both gantry systems and from plenoptic camera (Lytro Illum \([50]\)). We mainly compare our method with two depth-based methods, Kalantari et al. \([6]\) (depth-based) and LLFF \([9]\) (MPI representation) and four depth-independent methods, Wu et al. \([7]\), Yeung et al. \([11]\), HDDRNet \([25]\) and DA\(^2\)N \([62]\). The quantitative evaluations are reported by measuring the average PSNR and SSIM \([63]\) values over the synthesized views of the luminance channel in the YCbCr space. Please refer to the submitted video for more qualitative results.

A. Evaluations on Light Fields from Gantry Systems

1) Experiment settings: The comparisons are performed on 3D LFs from the MPI Light Field Archive \([15]\) and the CIVIT Dataset \([49]\). The resolutions of the datasets are 960 \( \times \) 720 \( \times \) 101 and 1280 \( \times \) 720 \( \times \) 193 (width, height and angular). In this experiment, we use two upsampling scale settings to evaluate the capability of the proposed Geo-NI: 16\( \times \) reconstruction using 7/13 views as input (MPI Light Field Archive \([15]\)/CIVIT Dataset \([49]\)) and 36\( \times \) reconstruction using 36 views as input. The depth hypotheses \( d \in D \) for the shearing operation are set to \{0, \pm 4, \pm 8, \pm 12, \pm 16\} for 16\( \times \) reconstruction and \{0, \pm 4, \pm 8, \pm 12, \pm 16, \pm 20, \pm 24, \pm 28\} for 36\( \times \) reconstruction, respectively.

Since the vanilla version of the network by Yeung et al. \([11]\] and Meng et al. \([26]\) (HDDRNet) were specifically designed for 4D LFs, we modify their convolutional layers to fit the 3D input while keeping its network architecture unchanged. We re-train the networks in the state-of-the-art methods (Kalantari et al. \([6]\), Yeung et al. \([11]\), LLFF \([9]\) and HDDRNet \([26]\) by using the same training dataset as the proposed Geo-NI. Due to the particularity of the training datasets, we compare DA\(^2\)N \([62]\) using the released network parameters. We perform network cascade to achieve different upsampling scales, i.e., two (three) cascades for 16\( \times \) (36\( \times \)) upsampling using a network of reconstruction factor \( \alpha = 4 \).

2) Qualitative comparison: Fig. 4 shows three reconstruction results on LFs (Bikes, FairyCollection and Workshop) from the MPI Light Field Archive \([15]\). And Fig. 5 shows the reconstruction results on LFs (Castle, Holiday and Flowers) from the CIVIT Dataset \([49]\). We demonstrate results with upsampling scale 16\( \times \) as well as 36\( \times \) on these two datasets.

In the modified implementation, every 8 (6) views are applied to reconstruct (synthesize) a 3D LF of 22 (21) views for the networks of reconstruction factor \( \alpha = 3 \) (\( \alpha = 4 \)).
Fig. 5. Comparison of the results on LFs from the CIVIT Dataset \cite{49} (reconstruction scales $16 \times$ and $36 \times$). The second column shows the ground truth EPI and the input EPI for $36 \times$ reconstruction.

### TABLE II

| Scale   | Kalantari et al. \cite{6} | Wu et al. \cite{7} | Yeung et al. \cite{11} | LLFF \cite{9} | HDDRNet \cite{25} | DA²N \cite{62} | Geo-NI (NI only) | Geo-NI (bilinear) | Geo-NI (U-net) | Geo-NI (ours) | Average |
|---------|----------------------------|-------------------|------------------------|--------------|------------------|--------------|----------------|----------------|--------------|--------------|---------|
| 16×     | 30.67 / 0.993              | 32.39 / 0.992     | 41.82 / 0.973          | 37.15 / 0.970 | 35.94 / 0.971    | 35.15 / 0.960 | 36.22 / 0.968  | 41.51 / 0.993 | 35.56 / 0.987 | 35.15 / 0.960 | 35.15 / 0.960 |
| 36×     | 35.07 / 0.978              | 38.76 / 0.991     | 46.96 / 0.997          | 41.52 / 0.993 | 41.85 / 0.996    | 41.21 / 0.993 | 35.56 / 0.987  | 35.15 / 0.960 | 35.15 / 0.960 | 35.15 / 0.960 | 35.15 / 0.960 |

### TABLE III

| Scale   | Seal & Balls | Castle | Holiday | Dragon | Flowers | Average |
|---------|--------------|--------|---------|--------|---------|---------|
| 16×     | 43.13 / 0.985 | 36.03 / 0.965 | 32.44 / 0.961 | 39.70 / 0.985 | 35.21 / 0.973 | 37.26 / 0.974 |
| 36×     | 45.72 / 0.997 | 41.26 / 0.992 | 38.21 / 0.991 | 47.85 / 0.997 | 42.19 / 0.995 | 43.44 / 0.995 |

### TABLE IV

| Scale   | Seal & Balls | Castle | Holiday | Dragon | Flowers | Average |
|---------|--------------|--------|---------|--------|---------|---------|
| 16×     | 38.01 / 0.977 | 32.95 / 0.948 | 29.11 / 0.928 | 35.49 / 0.975 | 32.51 / 0.959 | 33.61 / 0.957 |
| 36×     | 37.34 / 0.969 | 31.15 / 0.960 | 27.99 / 0.927 | 33.77 / 0.974 | 34.02 / 0.977 | 32.54 / 0.961 |
The maximum disparity range of the 36× reconstruction reaches 75 pixels in the *FairyCollection* case [15].

The qualitative comparisons indicate that the proposed Geo-NI framework is able to produce high-quality reconstruction on scenes with large disparities or non-Lambertian effects. The depth-based methods, Kalantari *et al.* [6] and LLFF [9], show high performance on simple structured scenes with large disparities while the depth-independent methods, HDDRNet [26] and DA²N [62], appear aliasing effects especially for 36× reconstruction, e.g., the WorkShop case in Fig. 3. For scenes with complex structures or non-Lambertian effects but with relatively small disparities, the depth-independent methods, HDDRNet [26] and DA²N [62], outperform the depth-based methods, Kalantari *et al.* [6] and LLFF [9], e.g., the cases Bikes and *FairyCollection* in Fig. 4 and the three cases in Fig. 5. However, the original structure or non-Lambertian effects will not be preserved in the results by the baseline methods when the input views are extremely sparse (36×). The proposed Geo-NI is able to effectively combine the advantages of depth-based methods and depth-independent methods, and produces plausible reconstruction results on challenge cases with large disparities, complex structures or non-Lambertian effects.

### 3) Quantitative comparison:

The quantitative results of 16× and 36× reconstructions for the MPI Light Field Archive [15] and the CIVIT Dataset [49] are shown in Table II and Table III respectively. For LFs with relatively small disparities (16× reconstruction), the methods without any depth information by Wu *et al.* [7], Yeung *et al.* [11] and Meng *et al.* [26] (HDDRNet) is comparable to the depth-based methods by Kalantari *et al.* [6] and Mildenhall *et al.* [9] (LLFF). However, the performances of the depth-free methods drop quickly when the disparity is large. For example, on the CIVIT Dataset [49] (Table III), the PSNR of the method by Wu *et al.* [7] is 3dB higher than the method by Kalantari *et al.* [6] for 16× reconstruction but 1dB lower for 36× reconstruction. Compared with the baseline methods, the proposed Geo-NI framework shows superior performance on both LF datasets.

### B. Evaluations on Light Fields from Lytro Illum

#### 1) Experiment settings:

The comparisons are performed on 4D LFs from three Lytro Illum datasets, the 30 Scenes dataset (30 LFs) by Kalantari *et al.* [6], and the Reflective (32 LFs) and Occlusions (51 LFs) categories from the Stanford Lytro Light Field Archive [64]. In this experiment, the upsampling factor is set to 7× using 2×2 views as input to reconstruct a 8×8 LF. The depth hypotheses d ∈ D for the shearing operation is set to {0, ±4, ±8, ±12, ±16}.

In addition to the methods evaluated in Sec. IV-A, we also compare the proposed Geo-NI framework with a depth-based method by Meng *et al.* [44]. Since the vanilla versions of the networks in [6, 11, 21, 26, 44] are trained on Lytro LFs, we use their released network parameters without re-training. The networks by Wu *et al.* [7] and Mildenhall *et al.* [9] (LLFF) are re-trained using the same dataset introduced in Sec. III-C2.

#### 2) Qualitative comparison:

Fig. 6 shows two results for 7× reconstruction (2×2 → 8×8) on LFs (Flower1 and IMG1743) from the 30 Scenes [6]. In the IMG1743 case, the maximum disparity reaches about 26 pixels between input views.

In the first case, the depth-independent methods by Yeung *et al.* [11] and DA²N [62] produce promising results due to the relatively small disparities. While the depth-base methods by Kalantari *et al.* [6] and LLFF [9] produce ghosting or tearing artifacts around occlusion boundaries. In the second case, the result by Yeung *et al.* [11] appears aliasing effects in the background due to the large disparity. While the DA²N [62] network generates blurry result as shown by the background door in the zoom-in figure and EPI. For the depth-based methods, the networks by Kalantari *et al.* [6] and LLFF [9] produce sever aliasing effects due to errors in depth estimation. The MPI-based method, LLFF [9], shows plausible result in the second case. However, the plane assignment error introduces tearing artifacts in the rendered view, as shown by the zoom-in figure. In comparison, the proposed Geo-NI framework provides reconstructed LFs with higher view consistency (as shown in the demonstrated EPIs).

#### 3) Quantitative comparison:

Table IV lists the quantitative results (PSNR/SSIM) averaged on LFs in each dataset. Limited by the baseline between viewpoints, the disparity range of LFs from Lytro Illum is smaller than that from gantry system, despite we only sample two viewpoints in each angular dimension, i.e., generally smaller than 14 pixels. Therefore, the depth-independent methods are able to achieve comparable or even superior performances than the depth-based methods. Since the DIBR network is able to elaborately select LFs from Lytro Illum is smaller than that from gantry system, the depth-independent methods are able to achieve comparable or even superior performances than the depth-based methods.

#### C. Ablation studies

In this subsection, we empirically investigate the modules in the proposed Geo-NI framework by performing the following ablation studies.

#### 1) Shear range:

We investigate the capability of the Geo-NI framework under different settings of shear range (range of shear amounts). We implement this experiment by evaluating the performance of the Geo-NI under different downsampling scales when choosing different ranges of shear amounts (depth hypotheses), where different downsampling scales will lead to different disparity ranges in the input LF. The result (evaluated...
Shear range
-48.48
-40.40
-32.32
-24.24
-16.16
-8.8
-4.4

Downsampling scale
4 8 16 24 32 40 48

![Fig. 6. Comparison of the results on LFs from Lytro Illum. The results show the reconstructed views, zoom-in regions and the EPIs at the location marked by red lines. LFs are Flowers1 and IMG1743 from the 30 Scenes [6]].

Fig. 7. The performance (PSNR) of the Geo-NI framework for different downsampling scales vs. different settings of shear range. Each grid shows the PSNR value (averaged on LFs from the MPI Light Field Archive [15]) of a certain downsampling scale under a certain setting of shear range.

on the MPI Light Field Archive [15]) is plotted in Fig. 4, where the horizontal axis denotes the downsampling scale and the vertical axis the shear range. The shear values are evenly sampled every 4 pixels within the range. The result shows that the proposed Geo-NI is able to achieve a high-quality reconstruction when a reasonable shear range is provided. For instance, for the downsampling scale 48, the disparity range averaged on the test LFs is around [-30, 35], the Geo-NI provides the best reconstruction results when the shear range is set to [-32, 32] or [-40, 40]. In addition, the result also indicates that the Geo-NI is robust to the settings of shear range. For example, for the downsampling scale 32 (averaged disparity range [-20, 23]), the quantitative result varies from 35.49dB to 35.53dB (0.04dB gap) when we set the shear range from [-24, 24] or [-48, 48]. Therefore, the proposed Geo-NI is able to generate satisfactory results even when an optimal shear range is not provided.

2) Neural interpolation only: This setting demonstrates the effectiveness of the DIBR part by detaching all components behind the NI network, which also equals to setting the depth hypotheses to zeros. We term this setting as “Geo-NI (NI only)” for short. As shown by the results in Table II and IV without using the proposed DIBR part, the Geo-NI (NI only) is able to perform high-quality reconstruction at small downsampling scale (please refer to results of 16× reconstruction in Table II III), even achieving the highest PSNR value on cases LivingRoom [15] and Seal & Balls [49]. But the performances deceases significantly when the input LFs become sparser, e.g., the PSNR decreases 2dB for 36× reconstruction on LFs from the MPI Light Field Archive [15]. On the other hand, it also indicates that the Geo-NI framework is able to enhance the performance of the NI network for LFs with large disparities via the selection of a proper shear amount.

3) Geo-NI with bilinear interpolation: In this experiment, we replace the NI network with a simple bilinear interpolation, denoted as “Geo-NI (bilinear)” for short. Benefiting from the perception of scene geometry in the DIBR part, the Geo-NI outperforms the most baseline methods at large downsampling scale (please refer to results of 36× reconstruction in Table II III and 7× reconstruction in Table IV), despite it does not use a powerful neural network for LF reconstruction. This ablation study further illustrates the efficacy of the DIBR part in the proposed Geo-NI framework.

4) Packing-unpacking structure: We validate the effectiveness of the proposed packing-unpacking structure by replacing it with a typical 3D U-net, denoted as “Geo-NI (U-net)” for short. Specifically, we discard the S2C-PS (C2S-PS) operations in the packing (unpacking) blocks, and use convolution (deconvolution) layers with stride 2 (1/2) to compress (restore) the spatial information. We also use skip connections between the encoder and decoder instead of those in the residual blocks to transmit the high frequency components. The dimensions of the network parameters are kept the same to the packing-unpacking network. As shown by the quantitative results listed in Table II III and IV the Geo-NI (U-net) also achieves a considerable performance with the help of the aliasing measurement mechanism in the DIBR part. However, the
Geo-NI with U-net suffers from performance degradation compared with the complete structure, which demonstrates the effectiveness of the packing-unpacking structure.

V. FURTHER ANALYSIS

In this section, we first introduce the byproduct of the proposed Geo-NI framework, i.e., depth rendering using reconstruction cost volume, then analyse the relation to conventional DIBR and learning-based DIBR.

A. Depth Map Rendering

The reconstruction cost in the DIBR network implicitly selects a proper shear amount (i.e., depth value) from the hypotheses, which is essentially similar with the purpose of matching cost. Therefore, the DIBR network, to some extent, can be interpreted as a depth estimator. In a standard depth estimation pipeline, the initial depth map can be extracted from the cost volume using the WTA strategy \[ \arg\min_{d \in \mathcal{D}} \mathcal{C}_d \], i.e.,

\[
D(x, y, s) = \sum_{d \in \mathcal{D}} d \cdot \sigma_d(-\mathcal{C}_d(x, y, s)).
\]  

(3)

It should be noted that the extracted depth \( D \) is a 3D tensor indicating the variation along the angular dimension.

Fig. 8 shows the rendered depth by using the reconstruction cost volume in the proposed Geo-NI framework. The second and the last rows demonstrate depth maps rendered using the raw reconstruction cost volumes and the filtered volumes using the classical cost volume filtering method proposed by Hosni et al. in [65]. The proposed Geo-NI is able to perceive the occlusion boundary despite the training objective of the networks is only LF rendering, as shown by the cases Occlusion1 and Occlusion18 in Fig. 8.

B. Relation to Depth-Image-based Rendering

1) Relation to conventional DIBR: Conventional DIBR methods first estimate the depth of the scene, then blend the warped views based on the scene geometry (depth). For the depth estimation, these methods typically construct a cost volume that records the matching cost of each pixel along the dimension of depth hypothesis. The depth of the scene is solved from the cost volume using Winner Takes All (WTA) strategy \[ \arg\min \], e.g., argmin operation. Instead of focusing on solving the depth, our idea is to render the desired LF directly from the cost volume.

But conventional cost volume in DIBR has following problems to reach our idea: i) The cost measures the correspondence between features, it cannot be used to synthesis novel views straightforwardly; ii) The cost is usually aggregated along the angular dimension, leading to dimension mismatching with the LF data. We address these problems by measuring the aliasing effects of the sheared LFs in replacing of the correspondences of a single view. On the one hand, measuring the aliasing effect in the DIBR network helps to guarantee the photo-consistency for Lambertian regions with large disparities, as shown in Fig. 9 (black arrow). On the other hand, it preserves the non-Lambertian effect reconstructed by the NI network since there is no assumption of depth consistency along the angular dimension, as shown in Fig. 9 (red arrow).

2) Relation to learning-based DIBR: Standard learning-based DIBR methods \[ 6, 43, 45, 46, 41 \] first estimate depth or optical flow via a neural network, and then refine the warped views or feature maps through another network to synthesize the novel view. The refinement network serves to correct the warping errors caused by the depth (flow) estimation network. However, when a region deviates too far from its proper position and the refinement network does not have a large enough receptive field, it will not be corrected.
datasets have demonstrated that the combination of NI and via spatial-channel pixel shuffling. Evaluations on various LF structure that effectively encodes and decodes LF features networks, we have designed a hierarchical packing-unpacking by the NI network can be maintained. For the NI and DIBR consistence between views, non-Lambertian effects reconstructed in the LFs. In addition, since we do not compel depth con-

DIBR network can be used to render scene depth of each view LF. We have shown that the reconstruction cost volume in the end-to-end optimization. In contrast, the method in [66] implant NI within the DIBR pipeline. While in [62], a fusion network is applied to directly blend the sheared EPIs without utilizing the concept of DIBR. The DIBR pipeline in the proposed framework is able to turn the deep neural network into a white box by explaining how the network weights each slice of sheared LF using reconstruction cost. Second, all the modules in our framework is differentiable, ensuring the end-to-end optimization. In contrast, the method in [60] uses non-differentiable post-processing to reconstruct the high-angular resolution LF. Third, the method in [60] requires depth propagation between views before the reconstruction. In the proposed Geo-NI framework, we measure the aliasing effects of the neural interpolated LFs to generate a 3D depth volume (as described in Eqn. 3) rather than a single view, which guarantees the view consistency in the rendered LFs.

VI. CONCLUSIONS

We have proposed a geometry-aware neural interpolation by launching a Neural Interpolation (NI) network within a Depth Image-Based Rendering (DIBR) pipeline. The NI network serves to reconstruct high angular resolution LFs which are sheared under a set of depth hypotheses. And the DIBR network is developed to construct a reconstruction cost volume through measuring the degrees of aliasing in the neural interpolated LFs, which is then applied for rendering the final LF. We have shown that the reconstruction cost volume in the DIBR network can be used to render scene depth of each view in the LFs. In addition, since we do not compel depth consistency between views, non-Lambertian effects reconstructed by the NI network can be maintained. For the NI and DIBR networks, we have designed a hierarchical packing-unpacking structure that effectively encodes and decodes LF features via spatial-channel pixel shuffling. Evaluations on various LF datasets have demonstrated that the combination of NI and DIBR pipeline is able to render high-quality LFs with large disparities and non-Lambertian effects.

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