MiNL: Micro-images based Neural Representation for Light Fields

Hanxin Zhu
University of Science and Technology of China
hanxinzhu@mail.ustc.edu.cn

Henan Wang
University of Science and Technology of China
henanwang@mail.ustc.edu.cn

Zhibo Chen
University of Science and Technology of China
chenzhibo@ustc.edu.cn

Abstract

Traditional representations for light fields can be separated into two types: explicit representation and implicit representation. Unlike explicit representation that represents light fields as Sub-Aperture Images (SAIs) based arrays or Micro-Images (MIs) based lenslet images, implicit representation treats light fields as neural networks, which is inherently a continuous representation in contrast to discrete explicit representation. However, at present almost all the implicit representations for light fields utilize SAIs to train an MLP to learn a pixel-wise mapping from 4D spatial-angular coordinate to pixel colors, which is neither compact nor of low complexity. Instead, in this paper we propose MiNL, a novel MI-wise implicit neural representation for light fields that train an MLP + CNN to learn a mapping from 2D MI coordinates to MI colors. Given the micro-image’s coordinate, MiNL outputs the corresponding micro-image's RGB values. Light field encoding in MiNL is just training a neural network to regress the micro-images, and the decoding process is a simple feedforward operation. Compared with common pixel-wise implicit representation, MiNL is more compact and efficient that has faster decoding speed (∼80–180 speed-up) as well as better visual quality (1–4dB PSNR improvement on average). With such a representation, all information of light fields are stored in parameters of neural networks, which can realize several light field-related tasks at the same time. For example, compared with mainstream light field compression methods that have complex processing pipeline, our proposed method transform the light field compression task into model compression task and can achieve comparable performance with state-of-the-art methods through a simple neural network training, with about 1–2dB PSNR improvement over HEVC/H.265 at the same bit rate. In addition to light field compression, MiNL can also be generalized to light field denoising, with more than 7dB PSNR improvement over original noisy light field images for different kinds of noises.

1 Introduction

Derived from the plenoptic function, a light ray can be parameterized by its intersections with two parallel planes, namely the spatial plane \((x, y)\) and the angular plane \((u, v)\). Thus light field contains
Figure 1: (a) Common pixel-wise implicit representation for light fields which takes 4D spatial-angular coordinate as input on the basis of SAIs (b) Our proposed method, MiNL, which takes 2D micro-image coordinate as input on the basis of MIs.

four-dimensional (4-D) information. With the additional dimensions compared to traditional 2-D images, light field images can bring us more applications such as refocusing and view synthesis, which can lead to more immersive experience in scenarios such as virtual reality (VR).

Normally light field images are captured by lenslet cameras. Different from conventional cameras, a micro-lens array is inserted between the main lens and the sensor plane. Each micro-lens captures a low resolution portion of the scene, namely a micro-image (MI) or macro-pixel. A light field image from Lytro camera is composed of 625×434 micro-images with 15×15 pixels inside each micro-image. By extracting pixels in the same position of each micro-image, we get a series of sub-aperture images (SAI), which can be regarded as photos captured by cameras from different viewing angles.

Whether MI-based or SAI-based representations, both of them share a common drawback: the enormous data. As mentioned above, a LF image from Lytro camera has 625×434 spatial resolution and 15×15 angular resolution. No matter one treats it as a huge image of size (9375, 6510) or 225 images of size (625, 434), it’s extremely inconvenient for transmission or storage. As a result, a more efficient representation for light field is severely demanded.

To solve the above-mentioned problem, we propose MiNL, a novel neural representation for light fields. As is shown in Figure[1], different from most common and naïve pixel-wise implicit representations for light fields that utilize sub-aperture images to construct a mapping from 4D spatial-angular coordinates to pixel colors [2, 4, 14, 16], MiNL is a MI-wise implicit representation which take advantage of micro-images to learn a mapping from 2D micro-image coordinates to micro-image colors. Compared with the traditional implicit representation, MiNL owns two significant advantages: low complexity and higher (or more compact) representation ability. Firstly, on account that one micro-image usually has hundreds of pixels, one feedforward process of MiNL is equivalent to hundreds of feedforward processes of pixel wise implicit representation, and thus the decoding speed of MiNL is much faster (∼80–180 speed-up). Secondly, just like the pixels in the blue box and the green box shown in the upper left corner of Figure[2], for pixels of different views correspond to spatial points that are close to each other with similar RGB values, their input coordinates deserve to be adjacent as well. In other words, distances of input coordinates for these spatially adjacent points should be as small as possible. However, this is not the case for pixel-wise SAI based implicit
Figure 2: Differences of input coordinates for SAI based pixel-wise implicit representation and MI based MI-wise implicit representation

representation, where two spatially adjacent points with almost the same colors can have quite different input coordinates, as demonstrated by the blue coordinate and the green coordinate in the upper right corner of Figure 2, which will lead to more model capacity to remember these meaningless differences. In contrast, for MI based implicit representation, i.e. MiNL, all pixels in one micro-image are inherently spatially adjacent points which have the same input coordinates, as shown in the purple box and the purple coordinates in Figure 2. Such a characteristic promises the superiority of our proposed method, where MiNL can achieve more compact representation for light fields and obtain higher visual quality under circumstances of the same model capacity compared with mostly adopted SAI based pixel-wise implicit representation nowadays.

Moreover, our proposed neural representation for light fields also has a great advantage over traditional light field representations, i.e. SAI or MI, and is able to realize several light field-related tasks through a simple neural network training. For example, to achieve light field compression, classical coding frameworks such as HEVC/H.265 usually treat all of the sub-aperture images as pseudo video sequences, followed by several processing modules such as key frames selection, residual calculation, discrete cosine transform, mode selection, predictive coding and so on to obtain the compressed light field images [31, 32, 43]. In addition to these hand-crafted coding method, view synthesis based methods are also popular for light field compression, where a few of key view SAI are selected to be coded in the coding process and the rest unselected SAI are synthesized in the decoding process [20, 22, 25]. All of these methods depend on a complex processing pipeline and the decoding operation is quite complicated as well. In contrast, MiNL leverages the model parameters of neural networks to store light field images, and thus transforms the light field compression task into model compression task. By means of several simple model compression techniques such as model pruning and model quantization, experimental results have demonstrated that MiNL can achieve comparable performance with state-of-the-art light field compression methods, with about 1~2dB PSNR improvement over HEVC/H.265 at the same bit rate.

In addition to light field compression, MiNL also shows its remarkable ability for light field denoising. Given several noisy light field images, one can obtain the denoised images simply by virtue of the direct neural network training as mentioned above, without any other operations. Extensive experiments are conducted for different light field images with different types of noises, the result shows more than 7dB PSNR improvement between original noisy images and the denosied images, which surpass some traditional filter-based denoising methods.

The main contributions of this paper can be summarized as follows:
• We propose a novel micro-image based neural representation for light fields, i.e. MiNL. MiNL leverages parameters of neural networks to store information of light fields, which is able to realize several light field related tasks through just a simple neural network training. As far as we know, MiNL is the first work that utilize micro-images instead of sub-aperture images to construct implicit neural representations for light fields.

• We discovered that micro-images based implicit representation is much more efficient than SAI-based implicit representation for representing light fields. Under condition of the same model capacity, MiNL owns the advantages of lower complexity and higher (or more compact) representation ability, promising the superiority of our proposed method.

• Compared with common SAI based pixel-wise implicit representations for light fields, MiNL is a MI-wise implicit representation that can achieve faster decoding speed (×80∼180 speed up) and better visual qualities (1∼4dB PSNR improvement).

• MiNL transforms the light field compression task into model compression task. By means of several model compression techniques, MiNL can achieve comparable performance with state-of-the-art light field compression methods, with more than 1∼2dB PSNR improvement over HEVC/H.265.

• Given the noisy light field images, MiNL can obtain the denoised output through a simple neural network training without any other operations. The results demonstrate more than 7dB denoising improvement in PSNR over original noisy images for different kinds of noises.

2 Related work

2.1 Coordinated-based implicit neural representation

Coordinated-based implicit neural representation has gained more and more attention since the success of [37]. In contrast to traditional discrete explicit representations such as mesh, point cloud and voxels, implicit representation is actually an continuous representation which is quite memory-efficient. As a rule, coordinated-based implicit neural representation is realized by training a neural network to learn a mapping from input coordinates to scene properties such as pixel colors [6, 30, 39], volume density [24, 37, 52] and signed distance [38]. For implicit representations of light fields, almost all the methods adopt a similar scheme that make use of SAIs to construct a mapping from 4D spatial-angular coordinates to pixel RGB values [2, 4, 16], which is neither compact nor efficient. Instead, in this paper, we propose a method based on MIs to realize a MI-wise implicit neural representation that learns a function from 2D MI coordinates to colors of all pixels in the MI, i.e. MiNL. Experimental results demonstrated the superiority of MiNL from the aspect of lower complexity and higher representation ability.

2.2 Light Field Compression

Due to the vast size, various compression solutions have been proposed to exploit redundancies of light field images. Here we divide them into lenslet-based methods and view-based methods.

Lenslet image compression methods As Figure 2 shows, a lenslet image contains a number of micro-images, forming repetitive patterns. Conti et al. [11] proposes a self-similarity (SS) compensated prediction to explore the correlations in MIs. Li et al. [31, 32] propose a method to predict MIs using a scheme similar to HEVC inter-frame prediction. Liu et al. [33] propose a content-based LF image-compression method with Gaussian process regression to improve the compression efficiency and accelerate the prediction procedure. Inspired by end-to-end image compression networks, Tong et al. [47] propose a end-to-end spatial-angular-decorrelated network (SADN) to take advantage of both spatial or angular consistency in lenslet images.

SAI compression methods SAI representation of light field can be viewed as an array of 2-D images. Thus it’s reasonable to organize these images in a specific order and treat them as a pseudo video sequence (PVS). Vieria et al. [49] organize SAIs in a PVS with different scan orders and encodes it with HEVC. Liu et al. [34] propose a 2-D hierarchical structure which divides SAIs into different coding layers according to their positions, then these SAIs are encoded by JEM encoder. Besides, view synthesis methods encodes only a few key SAIs and recovers the rest at the decoder side. Zhao et al. [43] pick a sparse set of SAIs and encodes them with HEVC. The rest SAIs are synthesized by a
linear approximation model using the key SAIs. Several deep learning based methods \[1\,25\,55\] are also proposed to utilize the CNN architecture to recover the discarded SAIs.

In this paper we propose a new approach to achieve the light field compression task. Instead of designing a complex architecture to compress the explicit form of light field images, we adopt an implicit form (i.e. MiNL) to represent light field images and then compress the model parameters directly. Combining a relatively simple network architecture and an efficient model compression scheme, our method can obtain better compression performance.

2.3 Model Compression

As mentioned above, in the form of implicit representation, the light field compression task can be converted into a model compression task. LeCun et al.\[26\] have shown that not all network parameters are necessary. Removing unimportant weights can shrink model size and reduce computational complexity, making it possible to deploy neural networks on resource-constrained devices. By compressing the implicit model, we can further reduce the bitrate while maintaining the image quality. Existing model compression schemes can be categorized into pruning and quantization \[7\,18\,27\,29\,35\,51\], low-rank approximation \[48\,53\], knowledge distillation \[8\,17\,19\,42\] and so on. In this paper, we take advantage of model pruning, model quantization and entropy coding to realize model compression.

3 Method

3.1 MI-wise implicit neural representation for lenslet image

As is illustrated above, in this paper we choose to leverage MIs to construct an implicit representation for light fields. Considering a lenslet image consists of $625 \times 434$ micro-images with $11 \times 11$ pixels inside each of them, we can treat it as one giant image composed of pixels whose resolution is $6875 \times 4774$ or one relative small image whose resolution is $625 \times 434$ composed of micro-images. For the former one, the implicit representation is still pixel-wise that learns a mapping from pixel coordinate to pixel colors, which will be quite time-consuming in the decoding process just like SAI-based pixel-wise implicit representation. Besides, because implicit representation tends to smooth the image, such a pixel-wise method will blur boundaries between different micro-images and lead to severe leakages from adjacent pixels, as shown by the blue box in the upper half of Figure 3. Instead, for the latter one, i.e. MiNL, implicit representation is realized by learning a mapping from the micro-image coordinate to the micro-image colors. Such a MI-wise implicit representation promises a faster decoding speed and will be leakage-free since micro-images are directly predicted rather than pixel by pixel, which is able to preserve the boundaries between different micro-images, as shown by the green box in the lower half of Figure 3.

Position encoding

As is demonstrated by \[37\], a direct training from raw input coordinates to scene properties will lead to quite poor results, where the whole image is excessively smoothed out. As a result, to obtain high frequency detailed information, the raw input coordinates need to be mapped to a high-dimensional space before being fed into the neural network. In this paper, we choose the so-called Position Encoding operation \[37\] which is based on the Fourier base

$$D = (\sin(2^0 \pi d), \cos(2^0 \pi d), \sin(2^1 \pi d), \cos(2^1 \pi d), \ldots, \sin(2^{L-1} \pi d), \cos(2^{L-1} \pi d)), \quad (1)$$

where $d$ represents the raw 2D input coordinate that is normalized between $[0, 1]$, \(D\) represents the embedded high-dimensional vector, \(L\) is a hyperparameter.

MiNL architecture

As is shown in Figure 1 and Figure 5, MiNL takes the 2D MI coordinate as input and outputs the corresponding colors of all pixels in the MI. Different from most common pixel-wise implicit representation that utilize one MLP to store scene information, in this paper we propose to make use of MLP + CNN in order to match the dimension of MI. To facilitate training of the neural network, a simple but important trick is that the activation functions for all layers of MLP and CNN are sine function, which is demonstrated by \[44\] that such a scheme will help improve the speed and robustness of the training process.
Loss function  In this paper, we adopt the following loss function to train our model, which is a combination of $l_2$ loss and regularization term:

$$\text{Loss} = \frac{1}{B} \sum_{i=0}^{B} ||M^\text{pre}_i - M^\text{gt}_i||_2 + \alpha ||\theta||_1, \quad (2)$$

where $B$ is the number of one batch, $M^\text{pre}_i$ is the $i$-th predicted micro-image by MiNL, $M^\text{gt}_i$ is the $i$-th ground truth micro-image, $\theta$ are model parameters and $\alpha$ is a hyperparameter that used to balance the distortion term and the regularization term.

3.2 Model compression

In this section, we introduce the model compression schemes used in MiNL. We adopt the model compression procedure introduced in [6], which includes model pruning, model quantization and entropy coding.

Pruning  Pruning is an efficient model compression method which can increase model sparsity by eliminating unnecessary weights. Here we adopt the pruning method proposed in [27]. It first calculates the layer-adaptive magnitude-based pruning (LAMP) score of each weight, which is a rescaled version of the weight magnitude, followed by a global pruning based on LAMP score

$$\hat{w}_i = \begin{cases} w_i, & \text{if } \text{score}(w_i) \geq \text{score}_{\text{thres}} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where $w_i$ is the $i$-th original model parameter, $\hat{w}_i$ is the $i$-th pruned model parameter, $\text{score}(w_i)$ is the LAMP score of the $i$-th original model parameter, $\text{score}_{\text{thres}}$ is the LAMP score threshold value for all model parameters.

Quantization  After model pruning, quantization procedure is executed to further reduce the bits needed for network parameters. A network parameter $\delta_i$ (usually FP-32) is mapped to a $b$-bit integer

$$Q(\delta_i) = \text{round}\left(\frac{\delta_i - \delta_{\text{min}}}{S}\right) \quad (4)$$

where 'round' is rounding the value to the closest integer, $S$ the scale factor, $\delta_{\text{max}}$ and $\delta_{\text{min}}$ the max and min value for the parameter tensor $\delta$. When decoding, parameter $\delta_i$ can recovered by

$$\hat{\delta}_i = Q(\delta_i) \ast S + \delta_{\text{min}} \quad (5)$$
Entropy Coding  After quantization, Huffman Coding\[23\] is adopted as entropy coding model to generate the final bitstream. Huffman Coding distributes different number of bits to parameter values based on their overall frequency and generates a codebook. Different from the processes above, this one is lossless and can recover the quantized parameters without any reconstruction loss.

| Method      | SIREN | SIGNET | NeRF | NeRV | COIN | MIP | MiNL(Ours) |
|-------------|-------|--------|------|------|------|-----|------------|
| Model parameters↓ | 200kB | 200kB  | 211kB | 218kB | 185kB | 199kB | 185kB      |
| PSNR/dB ↑     | 27.12 | 26.92  | 25.23 | 22.83 | 22.88 | 23.81 | 27.1     |
| SSIM ↑        | 0.852 | 0.854  | 0.811 | 0.784 | 0.794 | 0.772 | 0.875     |
| Decoding time ↓ | 360s  | 420s   | 290s  | 1.2s  | 187s  | 305s | 2.2s       |
| Model parameters↓ | 299kB | 299kB  | 260kB | 284kB | 268kB | 271kB | 270kB      |
| PSNR/dB ↑     | 27.89 | 27.8   | 25.76 | 26.4  | 25.63 | 25.06 | 28.89     |
| SSIM ↑        | 0.875 | 0.869  | 0.823 | 0.821 | 0.801 | 0.785 | 0.891     |
| Decoding time ↓ | 364s  | 427s   | 298s  | 1.6s  | 196s  | 320s | 2.4s       |
| Model parameters↓ | 385kB | 385kB  | 363kB | 384kB | 355kB | 360kB | 357kB      |
| PSNR/dB ↑     | 28.45 | 28.51  | 26.51 | 28.08 | 26.12 | 26.03 | 29.3      |
| SSIM ↑        | 0.891 | 0.888  | 0.847 | 0.861 | 0.849 | 0.804 | 0.901     |
| Decoding time ↓ | 371s  | 434s   | 303s  | 1.9s  | 203s  | 328s | 2.8s       |

4 Experimental results

4.1 Implementation details

In this paper, the ICME 2016 Grand challenge test dataset that has 12 light field images are selected to prove the effectiveness of our proposed method. The angular resolution and spatial resolution for each light filed image are $15 \times 15$ and $625 \times 434$ respectively. To avoid using the dark views associated to vignetting, we perform experiments on a subset of the light field images (i.e. central $11 \times 11$ views).

In our experiments, several neural networks with different model sizes are optimized for each light field image. We use the Adam optimizer with a learning rate begins at $1 \times 10^{-2}$ and decays gradually to $1 \times 10^{-4}$ over the course of optimization (other hyperparameters of the Adam optimizer are set to default values). The hyperparameter $L$ of Equation\[1\] is set to 40, which means that the dimension of the embedded high-dimensional input vector for MiNL is 160. The balance factor $\alpha$ of Equation\[2\] is set to 0.01. We train the neural network for 250 epochs, with batchsize of 5000. We evaluate the performance with two metrics: PSNR and SSIM. All experiments are run on NVIDIA GeForce RTX 3080 Laptop GPU, please refer to the Appendix for more experimental results.
4.2 Comparison with other implicit neural representations

We compare our proposed method, i.e., MiNL, with other common implicit neural representation methods for light fields on the ICME dataset. Specifically, COIN [14] is the most naive one where a direct mapping from raw 4D spatial-angular coordinate to pixel colors is constructed, NeRF [37] is an improvement over COIN where the Position Encoding operation is introduced, SIREN [44] and SIGNET [16] can be viewed as the state-of-the-art method that has the best visual quality nowadays. In addition to these SAI-based pixel-wise implicit representation, we also compare MiNL with an image-wise implicit neural representation (i.e., NeRV [6]). Moreover, to validate the necessity of constructing a MI-wise implicit representation for lenslet images, we perform experiments on pixel-wise implicit representation for lenslet image (i.e., MIP) as described in Figure 3 (a) and section 3.1.

For fair comparison, all these methods have the same training time and the dimension of the input coordinates of these methods are the same. As is demonstrated in Table 1, under the condition of the same model parameters, MiNL can outperform all the other methods on PSNR, SSIM and decoding time to a large extent, with about $1\sim4\,\text{dB}$ PSNR improvement and $\times80\sim180$ decoding time speed-up. It is worth noting that though NeRV can have a slightly faster decoding speed than our proposed method, its visual quality is quite poor, especially when the model parameters are small.

4.3 Light field compression

Model compression results As mentioned above, MiNL is able to transform the light field compression task into model compression task. To achieve the best compression performance, we firstly perform experiments on model pruning and model quantization to decide the optimal pruning ratio and quantized bit. As proved in Figure 4, the model of 8 bit quantization and 20% pruning rate can achieve almost the same performance with the original model with 32 bit quantization and no pruning, which we choose as the default setting for model compression. Entropy coding is a lossless coding method that can further reduce the model size by $10\% \sim 15\%$.

Light field compression results We compare our proposed method with other implicit representation methods, HEVC/H.265 (x.265) [40], JPEG Pleno 4D Predictive coding mode and JPEG Pleno 4D Transform coding mode [41] for light field compression. Among these methods, HEVC is a handcrafted coding method that treats all the light field images as pseudo video sequences, VM 2.0 (4D prediction) and VM 2.0 (4D transform) are methods with quite complex processing pipelines that are specially designed for light field compression by JPEG. Bit-per-pixel (bpp) is adopted to represent the compression ratio. Figure 5 shows the rate-distortion curves for different methods, where our proposed method can achieve comparable performance with the state-of-the-art method with a simple neural network training (1~2 dB PSNR improvement over HEVC and the best SSIM performance). Figure 6 shows the visualization of light field compression results for different methods, where our proposed method can recover more high-frequency detailed information. It is worth mentioning that
we only use quite simple model compression methods in MiNL, and we believe that a better model compression method will lead to a better light field compression performance.

### 4.4 Light field denoising

For light field denoising, as shown in Table 2 and Figure 7, MiNL can achieve more than 7dB PSNR improvement over the original noisy light field images by means of a simple neural network training, surpassing many traditional hand-crafted filters. It is worth noting that we only perform experiments on a model of fixed size, and if the model size grows bigger, the denosing effects of MiNL would be better.

### 5 Conclusion

In this paper, we present a novel micro-images based neural representation for light fields, i.e. MiNL. Different from most pixel-wise or image-wise implicit neural representations that take advantage of sub-aperture images to represent light fields, we are the first that leverage micro-images to realize MI-wise implicit representation for light fields. MiNL stores the whole light fields into parameters of neural networks and is able to realize several light field related tasks such as light field compression and light field denoising. Extensive experiments have demonstrated the superiority of our proposed method, i.e. low complexity and higher representation ability. Compared with common implicit neural representations nowadays, MiNL can obtain 1~4dB PSNR improvement and 80~180x faster decoding speed. For light field compression, MiNL transforms it into model compression task and
can achieve state-of-the-art performance compared with other implicit representation methods and hand-crafted coding method such as HEVC/H.265. For light field denoising, MiNL can obtain the denoised light field images through a simple neural network training, with more than 7dB PSNR improvement over the original noisy images. The main limitation of our proposed method is that MiNL is not a generalizable method, which means that different neural networks need to be trained to overfit different light field images. Although generalization is a common problem in most implicit neural representation methods, we believe that methods such as incorporating geometry prior would help solve this problem, which will be our future work.

References

[1] Nader Bakir, Wassim Hamidouche, Olivier Déforges, Khouloud Samrout, and Mohamad Khalil. Light field image compression based on convolutional neural networks and linear approximation. In 2018 25th IEEE International Conference on Image Processing (ICIP), pages 1128–1132. IEEE, 2018.

[2] Mojtaba Bemana, Karol Myszkowski, Hans-Peter Seidel, and Tobias Ritschel. X-fields: Implicit neural view-, light-and time-image interpolation. ACM Transactions on Graphics (TOG), 39(6):1–15, 2020.

[3] Chris Buehler, Michael Bosse, Leonard McMillan, Steven Gortler, and Michael Cohen. Unstructured lumigraph rendering. In Proceedings of the 28th annual conference on Computer graphics and interactive techniques, pages 425–432, 2001.

[4] Paramanand Chandramouli, Hendrik Sommerhoff, and Andreas Kolb. Light field implicit representation for flexible resolution reconstruction. arXiv preprint arXiv:2112.00185, 2021.

[5] Anpei Chen, Minye Wu, Yingliang Zhang, Nianyi Li, Jie Lu, Shenghua Gao, and Jingyi Yu. Deep surface light fields. Proceedings of the ACM on Computer Graphics and Interactive Techniques, 1(1):1–17, 2018.

[6] Hao Chen, Bo He, Hanyu Wang, Yixuan Ren, Ser Nam Lim, and Abhinav Shrivastava. Nerv: Neural representations for videos. Advances in Neural Information Processing Systems, 34, 2021.

[7] Shi Chen and Qi Zhao. Shallowing deep networks: Layer-wise pruning based on feature representations. IEEE transactions on pattern analysis and machine intelligence, 41(12):3048–3056, 2018.

[8] Tianqi Chen, Ian Goodfellow, and Jonathon Shlens. Net2net: Accelerating learning via knowledge transfer. arXiv preprint arXiv:1511.05641, 2015.

[9] Aleksandra Chuchvara, Attila Barsi, and Atanas Gotchev. Fast and accurate depth estimation from sparse light fields. IEEE Transactions on Image Processing, 29:2492–2506, 2019.

[10] Caroline Conti, Luís Ducla Soares, and Paulo Nunes. Dense light field coding: A survey. IEEE Access, 8:49244–49284, 2020.

[11] Caroline Conti, Luís Ducla Soares, and Paulo Nunes. Hevc-based 3d holoscopic video coding using self-similarity compensated prediction. Signal Processing: Image Communication, 42:59–78, 2016.

[12] Paul E Debevec, Camillo J Taylor, and Jitendra Malik. Modeling and rendering architecture from photographs: A hybrid geometry-and image-based approach. In Proceedings of the 23rd annual conference on Computer graphics and interactive techniques, pages 11–20, 1996.

[13] Elian Dib, Mikaël Le Pendu, and Christine Guillemot. Light field compression using fourier disparity layers. In 2019 IEEE International Conference on Image Processing (ICIP), pages 3751–3755. IEEE, 2019.

[14] Emilien Dupont, Adam Golioński, Milad Alizadeh, Yee Whye Teh, and Arnaud Doucet. Coin: Compression with implicit neural representations. arXiv preprint arXiv:2103.03123, 2021.
[15] Touradj Ebrahimi, Siegfried Foessel, Fernando Pereira, and Peter Schelkens. Jpeg pleno: Toward an efficient representation of visual reality. *Ieee Multimedia*, 23(4):14–20, 2016.

[16] Brandon Yushan Feng and Amitabh Varshney. Signet: Efficient neural representation for light fields. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 14224–14233, 2021.

[17] Jianping Gou, Baosheng Yu, Stephen J Maybank, and Dacheng Tao. Knowledge distillation: A survey. *International Journal of Computer Vision*, 129(6):1789–1819, 2021.

[18] Song Han, Jeff Pool, John Tran, and William Dally. Learning both weights and connections for efficient neural network. *Advances in neural information processing systems*, 28, 2015.

[19] Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2(7), 2015.

[20] Xinpeng Huang, Ping An, Fengyin Cao, Deyang Liu, and Qiang Wu. Light-field compression using a pair of steps and depth estimation. *Optics express*, 27(3):3557–3573, 2019.

[21] Xinpeng Huang, Ping An, Yilei Chen, Deyang Liu, and Liquan Shen. Low bitrate light field compression with geometry and content consistency. *IEEE Transactions on Multimedia*, 2020.

[22] Xinpeng Huang, Ping An, Liang Shan, Ran Ma, and Liquan Shen. View synthesis for light field coding using depth estimation. In *2018 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1–6. IEEE, 2018.

[23] David A Huffman. A method for the construction of minimum-redundancy codes. *Proceedings of the IRE*, 40(9):1098–1101, 1952.

[24] Wonbong Jang and Lourdes Agapito. Codenerf: Disentangled neural radiance fields for object categories. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 12949–12958, 2021.

[25] Chuanmin Jia, Xinfeng Zhang, Shanshe Wang, Shiqi Wang, and Siwei Ma. Light field image compression using generative adversarial network-based view synthesis. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, 9(1):177–189, 2018.

[26] Yann LeCun, John Denker, and Sara Solla. Optimal brain damage. *Advances in neural information processing systems*, 2, 1989.

[27] JaeHo Lee, Sejun Park, Sangwoo Mo, Sungsoo Ahn, and Jinwoo Shin. Layer-adaptive sparsity for the magnitude-based pruning. In *International Conference on Learning Representations*, 2021.

[28] Marc Levoy and Pat Hanrahan. Light field rendering. In *Proceedings of the 23rd annual conference on Computer graphics and interactive techniques*, pages 31–42, 1996.

[29] Hao Li, Asim Kadav, Igor Durdanovic, Hanan Samet, and Hans Peter Graf. Pruning filters for efficient convnets. *arXiv preprint arXiv:1608.08710*, 2016.

[30] Jiaxin Li, Zijian Feng, Qi She, Henghui Ding, Changhu Wang, and Gim Hee Lee. Mine: Towards continuous depth mpi with nerf for novel view synthesis. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 12578–12588, 2021.

[31] Yun Li, Roger Olsson, and Mårten Sjöström. Compression of unfocused plenoptic images using a displacement intra prediction. In *2016 IEEE International Conference on Multimedia Expo Workshops (ICMEW)*, pages 1–4, 2016.

[32] Yun Li, Mårten Sjöström, Roger Olsson, and Ulf Jennehag. Coding of focused plenoptic contents by displacement intra prediction. *IEEE Transactions on Circuits and Systems for Video Technology*, 26(7):1308–1319, 2016.

[33] Deyang Liu, Ping An, Ran Ma, Wenfa Zhan, Xinpeng Huang, and Ali Abdullah Yahya. Content-based light field image compression method with gaussian process regression. *IEEE Transactions on Multimedia*, 22(4):846–859, 2020.
[34] Dong Liu, Lizhi Wang, Li Li, Zhiwei Xiong, Feng Wu, and Wenjun Zeng. Pseudo-sequence-based light field image compression. In 2016 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), pages 1–4. IEEE, 2016.

[35] Junjie Liu, Zhe Xu, Runbin Shi, Ray CC Cheung, and Hayden KH So. Dynamic sparse training: Find efficient sparse network from scratch with trainable masked layers. arXiv preprint arXiv:2005.06870, 2020.

[36] Ben Mildenhall, Pratul P Srinivasan, Rodrigo Ortiz-Cayon, Nima Khademi Kalantari, Ravi Ramamoorthi, Ren Ng, and Abhishek Kar. Local light field fusion: Practical view synthesis with prescriptive sampling guidelines. ACM Transactions on Graphics (TOG), 38(4):1–14, 2019.

[37] Ben Mildenhall, Pratul P Srinivasan, Matthew Tancik, Jonathan T Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In European conference on computer vision, pages 405–421. Springer, 2020.

[38] Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, and Steven Lovegrove. Deepsdf: Learning continuous signed distance functions for shape representation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 165–174, 2019.

[39] Keunhong Park, Utkaorth Sinha, Jonathan T Barron, Sofien Bouaziz, Dan B Goldman, Steven M Seitz, and Ricardo Martin-Brualla. Nerfies: Deformable neural radiance fields. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 5865–5874, 2021.

[40] Fernando Pereira, Carla Pagliari, Eduardo da Silva, Ioa Tabus, Hadi Amirpour, Marco Bernardo, and Antonio Pinheiro. Jpeg pleno light field coding common test conditions. In Standard ISO/IEC JTC 1/SC29/WG1N84025, 84th Meeting, 2019.

[41] Cristian Perr, Pekka Astola, Eduardo AB da Silva, Hesam Khanmohammad, Carla Pagliari, Peter Schelkens, and Ioa Tabus. Performance analysis of jpeg pleno light field coding. In Applications of Digital Image Processing XLII, volume 11137, page 111371H. International Society for Optics and Photonics, 2019.

[42] Adriana Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio. Fitnets: Hints for thin deep nets. arXiv preprint arXiv:1412.6550, 2014.

[43] Zhao Shengyang and Zhibo Chen. Light field image coding via linear approximation prior. pages 4562–4566, 09 2017.

[44] Vincent Sitzmann, Julien Martel, Alexander Bergman, David Lindell, and Gordon Wetzstein. Implicit neural representations with periodic activation functions. Advances in Neural Information Processing Systems, 33:7462–7473, 2020.

[45] Pratul P Srinivasan, Richard Tucker, Jonathan T Barron, Ravi Ramamoorthi, Ren Ng, and Noah Snavely. Pushing the boundaries of view extrapolation with multiplane images. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 175–184, 2019.

[46] Pratul P Srinivasan, Tongzhou Wang, Ashwin Sreelal, Ravi Ramamoorthi, and Ren Ng. Learning to synthesize a 4d rgbd light field from a single image. In Proceedings of the IEEE International Conference on Computer Vision, pages 2243–2251, 2017.

[47] Kedeng Tong, Xin Jin, Chen Wang, and Fan Jiang. Sadn: Learned light field image compression with spatial-angular decorrelation. In ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 1870–1874. IEEE, 2022.

[48] Andrew Tulloch and Yangqing Jia. High performance ultra-low-precision convolutions on mobile devices. arXiv preprint arXiv:1712.02427, 2017.

[49] Alexandre Vieira, Helder Duarte, Cristian Perr, Luis Tavora, and Pedro Assuncao. Data formats for high efficiency coding of lytro-illum light fields. In 2015 international conference on image processing theory, tools and applications (IPTA), pages 494–497. IEEE, 2015.
[50] Qianqian Wang, Zhicheng Wang, Kyle Genova, Pratul P Srinivasan, Howard Zhou, Jonathan T Barron, Ricardo Martin-Brualla, Noah Snavely, and Thomas Funkhouser. Ibrnet: Learning multi-view image-based rendering. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4690–4699, 2021.

[51] Wei Wen, Chunpeng Wu, Yandan Wang, Yiran Chen, and Hai Li. Learning structured sparsity in deep neural networks. Advances in neural information processing systems, 29, 2016.

[52] Qiangeng Xu, Zexiang Xu, Julien Philip, Sai Bi, Zhixin Shu, Kalyan Sunkavalli, and Ulrich Neumann. Point-nerf: Point-based neural radiance fields. arXiv preprint arXiv:2201.08845, 2022.

[53] Xiangyu Zhang, Jianhua Zou, Xiang Ming, Kaiming He, and Jian Sun. Efficient and accurate approximations of nonlinear convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and pattern Recognition, pages 1984–1992, 2015.

[54] Yongbing Zhang, Huijin Lv, Yebin Liu, Haoqian Wang, Xingzheng Wang, Qian Huang, Xingguang Xiang, and Qionghai Dai. Light-field depth estimation via epipolar plane image analysis and locally linear embedding. IEEE Transactions on Circuits and Systems for Video Technology, 27(4):739–747, 2016.

[55] Zhenghui Zhao, Shanshe Wang, Chuanmin Jia, Xinfeng Zhang, Siwei Ma, and Jiansheng Yang. Light field image compression based on deep learning. In 2018 IEEE International Conference on Multimedia and Expo (ICME), pages 1–6. IEEE, 2018.

[56] Tinghui Zhou, Richard Tucker, John Flynn, Graham Fyffe, and Noah Snavely. Stereo magnification: Learning view synthesis using multiplane images. arXiv preprint arXiv:1805.09817, 2018.

[57] Tinghui Zhou, Shubham Tulsiani, Weilun Sun, Jitendra Malik, and Alexei A Efros. View synthesis by appearance flow. In European conference on computer vision, pages 286–301. Springer, 2016.

[58] Wenhui Zhou, Enci Zhou, Gaomin Liu, Lili Lin, and Andrew Lumsdaine. Unsupervised monocular depth estimation from light field image. IEEE Transactions on Image Processing, 29:1606–1617, 2019.
A Appendix

A.1 Results on different light field images

We perform experiments on different light field images (*i.e.* Danger_de_Mort, Stone_Pillars_Outside and Fountain&Vincent2) to validate the superiority of MiNL, as demonstrated by the following results on light field compression.

![Danger_de_Mort](image1)

![Stone_Pillars_Outside](image2)

![Fountain&Vincent2](image3)

Figure 8: Different light field images used in our experiments

**Danger_de_Mort**

![RD Curve for Danger_de_Mort](image4)

Figure 9: Light field compression results of different methods on Danger_de_Mort

![Visualization of light field compression results of different methods on Danger_de_Mort](image5)

Figure 10: Visualization of light field compression results of different methods on Danger_de_Mort
Stone_Pillars_Outside

Figure 11: Light field compression results of different methods on Stone_Pillars_Outside

Figure 12: Visualization of light field compression results of different methods on Stone_Pillars_Outside

Fountain&Vincent2

Figure 13: Light field compression results of different methods on Fountain&Vincent2
Figure 14: Visualization of light field compression results of different methods on Fountain&Vincent2