View Sub-sampling and Reconstruction for Efficient Light Field Compression

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Abstract

Compression is an important task for many practical applications of light fields. Although previous work has proposed numerous methods for efficient light field compression, the effect of view selection on this task is not well exploited. In this work, we study different sub-sampling and reconstruction strategies for light field compression. We apply various sub-sampling and corresponding reconstruction strategies before and after light field compression. Then, fully reconstructed light fields are assessed to evaluate the performance of different methods. Our evaluation is performed on both real-world and synthetic datasets, and optimal strategies are devised from our experimental results. We hope this study would be beneficial for future research such as light field streaming, storage, and transmission.

Keywords: Light Field View Synthesis, Light Field Compression

1 Introduction

A 4D light field is described as a collection of light rays passing through a 3D volume with specific intensity and direction, which can be represented as the interaction between each ray and two parallel planes: image plane and camera plane. The original concept of 4D light fields was firstly introduced by Levoy et. al. in 1996 [Levoy and Hanrahan, 1996]. After years of active research, light fields were applied in various immersive visual applications such as VR, 3DTV and holographic systems. The capturing process of the light field usually produces a huge amount of data, which requires plenty of storage space and transmission bandwidth. To reduce these, efficient compression of light field data is crucial for practical applications. One potential way to compress light field data is to sub-sample sub-aperture views for encoding, and to reconstruct the missing views after decoding, which is enabled through advances in light field view synthesis. In this paper, we study different sub-sampling strategies in combination with a recent view synthesis method based on deep learning.

2 Related Work

Light field compression is a crucial research topic, due to the huge amount of data needed for light field imaging. Conti et. al. provided a thorough review about recent light field coding techniques [Conti et al., 2020]. One common approach is utilizing light field reconstruction methods to complete view-subsampled light fields, i.e. compressing only a subset of the original views [Chen et al., 2017, Zhao and Chen, 2017, Viola et al., 2018, Jiang et al., 2017b, Jiang et al., 2017a]. Various methods use a video codec such as HEVC as coding component, while JPEG launched the JPEG Pleno initiative for standardizing compression of plenoptic data including light fields [Ebrahimi et al., 2016].

Recently, deep learning techniques were introduced to light field compression. Chen et. al. investigate the impact of subsampling and reconstruction on the light field view synthesis [Chen et al., 2020b]. Chen et. al.
proposed a self-supervised learning method to synthesize novel views of light field [Chen et al., 2020a]. Zhao et. al. presented a learning-based method which combines view enhancement and view synthesis to reconstruct complete light fields from decoded views [Zhao et al., 2018]. Wafa et. al. proposed a deep recursive residual network to synthesize intermediate views after the sparse views are decoded [Wafa et al., 2021]. Singh et. al. introduced an end-to-end disparity-aware 3D-CNN for light field compression, which utilizes the disparity information between views and the middle view [Singh and Rameshan, 2021]. Other works target light field compression using adversarial learning [Jia et al., 2018, Bakir et al., 2020, Liu et al., 2021].

All aforementioned approaches perform light field compression with one certain pattern of sub-aperture views, but we argue that the impact of different sub-sampling patterns on compression performance would be worth investigating. Thus, in this paper, we focus on evaluating view selection strategies for light field compression.

3 Subsampling and reconstruction for efficient light field compression

In this section, we present different sub-sampling and reconstruction strategies for light field compression. We first select various sub-sampling strategies, then the sub-sampled views are encoded, and finally the light field is completed by view synthesis.

3.1 Sub-sampling and Encoding

With the classical two-plane representation of light fields, three basic view sub-sampling strategies are introduced, row, column and corners, as shown in Fig. 2. Each one of them will have their corresponding reconstruction process, as discussed in Section 3.2. We further investigate different sub-sampling densities (2x) and (4x). The remaining views after sub-sampling are scanned in snake order Fig. 3a and encoded with a video codec.

3.2 Decoding and Reconstruction

After decoding at the receiver, we perform reconstruction by inverting the corresponding sub-sampling strategies. We take corners_4x of a 9 × 9 light field as an example, as shown in Fig. 5b. The complete reconstruction process is a cascade of one row wise and one column wise view synthesis, while (4x) reconstruction is a cascade of two (2x) interpolations. For row and column based sub-sampling, it is simple to apply row wise and column wise interpolation to complete the light field, accordingly.
Figure 2: Six strategies to sub-sample views from a $9 \times 9$ light field. Sub-sampled views are shown in green. The columns show three different type of strategies (row, column and corners). Top (2x) and bottom (4x) rows illustrate different sampling densities.

4 Experiments

In this section, we present the details of our experiments. All computations were performed on an Intel Core i7-6700k 4.0GHz CPU. To implement our pipeline, sub-sampled RGB views were converted into YUV 420 video using the open-source FFMPEG software [FFM]. Then, these video files were encoded by an efficient video codec, HM (HEVC) 16.22 [HEV]. We used typical quantization parameters to vary bitrate and quality (QP: 20, 25, 30, 35, 40, 45). As baseline comparison we also present the results of encoding the full light field without any sub-sampling and reconstruction, which is indicated as “anchor” in all the figures.

We performed all experiments with synthetic light fields, Lytro images, and gantry-robot captured data to investigate different properties. The **Bedroom** light field is from the widely used synthetic HCI dataset. **Bee_2** is extracted from the Lytro Illum dataset using a Lytro enhancement pipeline [Matysiak et al., 2018]. **LegoKnight** is from the Stanford dataset and pre-cropped to $512 \times 512$ to have similar spatial resolution to other light fields. This is a challenging light field due to its large disparity compared to others and extended textureless areas. From all light fields we used $9 \times 9$ views.

Figure 3 shows the PSNR results after reconstruction as heatmaps, for 6 different strategies. These light fields were reconstructed by the state-of-the-art synthesis method CycleLF [Chen et al., 2020a] with $QP = 30$. We can recognize the sub-sampling patterns in these results, as directly decoded views have higher PSNR than interpolated views. These quality fluctuations are analyzed in more detail in Figure 7 where we show the standard deviations of PSNR results over the whole range of bitrates. We find that anchor encoding has the lowest fluctuation as expected. Fluctuations increase with the sub-sampling ratio as can also be expected, i.e. (4x) versions exhibiting highest fluctuations. While overall fluctuations are quite low for HCI and Lytro, they are significant for the relatively sparse Lego Knights. Thus, quality fluctuations have to be considered when applying view sub-sampling for light field compression.
Complete Rate-distortion (RD) results for PSNR and SSIM over bitrate are shown in Figure 5 and Figure 6, respectively. All strategies with CycleLF outperform bilinear on all three datasets. All strategies with CycleLF reconstruction outperform anchor encoding on Bedroom and show equivalent performance on Bee_2. Strategies with CycleLF reconstruction fall behind the anchor for LegoKnight, because of the large baseline of this light field affecting the performance of the reconstruction method. Meanwhile, regarding SSIM, CycleLF-based strategies consistently outperform the anchor.

Bjontegaard metrics (BD-PSNR and BD-Rate) [Wien, 2015] are shown in Table 1 and Table 2 including a number of additional light fields. Compression with sub-sampling and CycleLF reconstruction consistently outperforms the anchor. Especially on the HCI dataset, the CycleLF-based method achieves an average BD-DSNR gain of 1.63dB and an average BD-DSNR bitrate saving of -53.6% over anchor compression with the “corner_4x” pattern. Please note that we can’t show BD-scores for the Stanford dataset as the large differences between the involved RD curves make this metric unsuitable for this case [Wien, 2015].
Figure 4: PSNR scores after light field reconstruction with \( QP = 30 \). Top, middle and bottom rows show results from HCI (Bedroom), Lytro (Bee_2) and Stanford (Lego Knights) datasets using CycleLF [Chen et al., 2020a].

Figure 5: Rate-distortion results as PSNR over bit per pixel (bpp). Top row, middle row and bottom row are results on HCI (Bedroom), Lytro (Bee_2) and Stanford (Lego Knights), respectively.

Figure 6: Rate-distortion results as Structural Similarity Index (SSIM) over bit per pixel (bpp). Top row, middle row and bottom row are results on HCI (Bedroom), Lytro (Bee_2) and Stanford (Lego Knights), respectively.

5 Conclusion

In this paper we presented a comprehensive investigation about the influence of different view selection strategies on the light field compression task. To achieve this goal, we tested our complete pipeline including sub-sampling, encoding, decoding, and reconstruction with various strategies. Our results show that sub-sampling can improve compression efficiency, especially for dense light fields. Higher sub-sampling can give more gain.
Figure 7: Per-view standard deviations of PSNR results over bitrate. Left, middle and right for HCI (Bedroom), Lytro (Bee_2) and Stanford (Lego Knights), respectively.

|    | Bed | Bic | Her | Ori | avg |
|----|-----|-----|-----|-----|-----|
| row_2x | BD-PSNR | 0.68 | 0.60 | 0.51 | 0.47 | 0.57 |
|      | BD-Rate | -24.8 | -22.6 | -21.4 | -22.3 | -22.8 |
| row_4x | BD-PSNR | 1.47 | 1.27 | 0.89 | 1.08 | 1.18 |
|      | BD-Rate | -48.0 | -43.8 | -36.9 | -44.6 | -43.4 |
| col_2x | BD-PSNR | 0.91 | 0.96 | 0.78 | 0.78 | 0.86 |
|      | BD-Rate | -31.5 | -32.7 | -30.0 | -33.0 | -31.8 |
| col_4x | BD-PSNR | 1.79 | 1.72 | 1.26 | 1.54 | 1.58 |
|      | BD-Rate | -53.8 | -51.6 | -46.1 | -55.0 | -51.6 |
| cors_2x | BD-PSNR | 1.66 | 1.56 | 1.24 | 1.26 | 1.43 |
|      | BD-Rate | -51.6 | -48.4 | -44.8 | -49.3 | -48.5 |
| cors_4x | BD-PSNR | 1.62 | 1.89 | 1.28 | 1.76 | 1.63 |
|      | BD-Rate | -52.7 | -55.3 | -48.2 | -58.2 | -53.6 |

Table 1: BD-scores of CycleLF reconstruction on the HCI dataset, compared to baseline compression.

|    | Bee | Bik | Che | Des | avg |
|----|-----|-----|-----|-----|-----|
| row_2x | BD-PSNR | 0.28 | 0.47 | 0.58 | 0.30 | 0.49 |
|      | BD-Rate | -18.1 | -20.8 | -28.9 | -19.7 | -24.8 |
| row_4x | BD-PSNR | 0.36 | 0.89 | 1.11 | 0.59 | 0.63 |
|      | BD-Rate | -29.4 | -39.8 | -52.7 | -42.2 | -36.4 |
| col_2x | BD-PSNR | 0.50 | 0.61 | 0.59 | 0.23 | 0.55 |
|      | BD-Rate | -29.3 | -25.7 | -29.5 | -17.1 | -27.9 |
| col_4x | BD-PSNR | 0.68 | 0.89 | 1.00 | 0.34 | 0.48 |
|      | BD-Rate | -41.6 | -41.3 | -52.0 | -36.6 | -36.6 |
| cors_2x | BD-PSNR | 0.63 | 1.05 | 1.18 | 0.52 | 0.97 |
|      | BD-Rate | -39.1 | -43.7 | -54.1 | -40.7 | -47.3 |
| cors_4x | BD-PSNR | 0.45 | 0.90 | 1.17 | 0.24 | 0.40 |
|      | BD-Rate | -40.6 | -43.2 | -52.8 | -37.8 | -37.3 |

Table 2: BD-scores of CycleLF reconstruction on the Lytro dataset, compared to baseline compression.

in these cases. However, fluctuations of output view quality have to be considered, which increase with the sub-sampling ratio.

Acknowledgments

All authors are from the Trinity College Dublin, College Green, Ireland. Contact cheny5@tcd.ie for further questions about this work. This publication has emanated from research conducted with the financial support of Science Foundation Ireland (SFI) under the Grant Number 15/RP/2776. We also gratefully acknowledge the support of NVIDIA Corporation with the donation of the Titan Xp GPU used for this research. 978-1-7281-9320-5/20/$31.00 2020 European Union

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