AN INTEGRATED REPRESENTATION & COMPRESSION SCHEME BASED ON CONVOLUTIONAL AUTOENCODERS WITH 4D-DCT PERCEPTUAL ENCODING FOR HIGH DYNAMIC RANGE LIGHT FIELDS

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Sally Khaidem
Department of Electrical Engineering
Indian Institute of Technology Madras
Chennai 600036, India
ee20d041@smail.iitm.ac.in

Mansi Sharma
Department of Electrical Engineering
Indian Institute of Technology Madras
Chennai 600036, India
mansisharma@ee.iitm.ac.in

ABSTRACT

The emerging and existing light field displays are highly capable of realistic presentation of 3D scenes on auto-stereoscopic glasses-free platforms. The light field size is a major drawback while utilising 3D displays and streaming purposes. When a light field is of high dynamic range, the size increases drastically. In this paper, we propose a novel compression algorithm for a high dynamic range light field which yields a perceptually lossless compression. The algorithm exploits the inter and intra view correlations of the HDR light field by interpreting it to be a four-dimension volume. The HDR light field compression is based on a novel 4DDCT-UCS (4D-DCT Uniform Colour Space) algorithm. Additional encoding of 4DDCT-UCS acquired images by HEVC eliminates intra-frame, inter-frame and intrinsic redundancies in HDR light field data. Comparison with state-of-the-art coders like JPEG-XL and HDR video coding algorithm exhibits superior compression performance of the proposed scheme for real-world light fields.

Keywords 4D-DCT · Coded Aperture · HDR · HEVC · Light Field · Transform Coding

1 Introduction

Figure 1: Schematic diagram of a coded aperture camera.

The light field imaging in the latest generation of auto-stereoscopic and glasses-free displays have revamped their performance in rendering 3D scenes and contents. The support for continuous motion parallax, greater depth-of-field and a wider field-of-view enable computational multi-view light field displays to offer a more realistic viewing experience [Watanabe et al., 2019]. Imaging of high dynamic range (HDR) light field is relatively an unexplored domain due to the computational expensiveness as compared to a low dynamic range (LDR) light field compression algorithms and lack
of hardware that can fully utilise and display the HDR content. There is a growing necessity for efficient representation and coding pipelines for HDR light field data that are suitable for 3D displays and high fidelity streaming applications.

This paper focuses on an efficient representation and compression of HDR light field using our novel 4D-DCT Uniform Colour Space (4DDCT-UCS) scheme. The complete workflow of the proposed scheme is illustrated in Fig. 2. The coded aperture camera shown in Fig. 1 is simulated to obtain acquired images from the HDR light field Veeraraghavan et al. [2007], Inagaki et al. [2018]. The module of acquiring HDR light field is based on an auto-encoder framework Vincent et al. [2008]. The encoder and decoder network are connected and are trained to achieve the best identity mapping between the input and the output. The light field gets reduced to two acquired images through the physical imaging process of a coded aperture camera system. Reconstruction of the light field is performed utilising the acquired images. The 4DDCT-UCS algorithm compresses the acquired images by applying 4D Discrete Cosine Transform (DCT) Dlabaja [2019] for efficient entropy encoding Lee and Choe [2022]. Further encoding based on perception is performed by linearly scaling of Luma and non-linear scaling Chroma component in the perceptually uniform Intensity, Protan and Tritan (IPT) colour opponent space Ebner and Fairchild [1998]. The proposed 4DDCT-UCS algorithm allows incremental streaming of the acquired image to the receiver at every time instant. High Efficiency Video Coding (HEVC) Sullivan et al. [2012] is used to achieve additional encoding by reducing the inter-frame, intra-frame and other intrinsic redundancies present in the light field. The performance of the proposed scheme is being compared with JPEG-XL Alakuijala et al. [2020] and ours is significantly superior. It is inferred from the experimental results provided in section 3 that our proposed algorithm is capable of capturing and high-quality reconstruction of HDR light field from a reduced number of acquired images. The main advantages of the proposed algorithm are:

- 4DDCT-UCS effectively reduces the inter and intra frame redundancies present in the acquired images by applying 4D DCT and effectively compressing high frequencies and low frequencies separately.
- The proposed scheme works with less number of images instead of working with the entire HDR light field, thus drastically reducing the computational cost.
- 4DDCT-UCS can achieve a high PSNR value at lower bit rates and lower total bytes.

2 Proposed work

In this section, a novel representation and coding of an HDR light field is proposed. The workflow can be divided into three main components. BLOCK I represents the CNN that reduces the light field into acquired images through a physical imaging process of the coded aperture camera. Block II represents the compression of redundant information present in the acquired images through 4D-DCT and perceptual coding the Luma component and linearly scaling the Chroma component for effective compression. In Block III, the decoding of the encoded light field is performed. The complete flow of the proposed pipeline is explained as follows.

2.1 Light Field to Acquired Images

The 4D light field \( L(u,v,s,t) \) is defined by the intersection of light into the two parallel planes \((u,v)\) and \((s,t)\) Levoy and Hanrahan [1996]. A coded aperture camera uses the images acquired through various aperture patterns to computationally construct the light field Inagaki et al. [2018]. Fig. 1 illustrates the schematic diagram of a coded aperture camera capturing the incoming light rays by adopting a coordinate system, where \((u,v)\) and \((s,t)\) are imaging...
A quantization matrix is applied on the coefficients as denoted in (7), where

\[ a_n(u, v) = \int \int r_n(s, t) L(s, t, u, v) ds dt \]

\[ = \int \int r_n(s, t) l_{s,t}(u, v) ds dt \]

Discretising the aperture plane \((s, t)\), the acquired image formed is simplified as

\[ a_n(u, v) = \sum_{s,t} r_n(s, t) l_{s,t}(u, v) \]

The entire light field reconstruction is equivalent to estimating \(M = 25\) sub-aperture views from \(N = 2\) acquired images \(a_n(u, v)\). The auto-encoder framework implemented using Chainer [Tokui et al., 2015] is trained on samples from 51 light field datasets. The mapping function of the coded aperture camera acquisition process (2) can be formulated as

\[ f : X \rightarrow Y \]

where, \(X\) is the vector containing all pixels of \(l_m(u, v)\) for all \(m \in \{1, ..., M\}\). The \(X\) vector length for an image having dimensions \(p \times q\) is \(p \times q \times M\). The vector \(Y\) represents all the pixel in \(a_n(u, v)\) for all \(n \in \{1, ..., N\}\) and the reconstruction mapping is denoted as

\[ g : Y \rightarrow \hat{X} \]

The estimate of \(X\) is represented by \(\hat{X}\). Under the condition that \(N \ll M\), the composite mapping function \(h = g \circ f\) must be close to identity as possible, where \(f\) and \(g\) represent the encoder and decoder of the auto-encoder respectively. The objective of the optimization is expressed with square loss error as

\[ \text{argmin}_{f,g} |X - \hat{X}|^2 = \text{argmin}_{f,g} \sum_{m} \sum_{u,v} |l_m(u,v) - \hat{l}_m(u,v)|^2 \]

where, \(\hat{l}_m(u,v)\) is the estimate of \(l_m(u,v)\). The composite mapping \(h = g \circ f\) is implemented using 2D convolutional layers. Aperture patterns \(r_n(u, v)\) are optimised following the parameters learned in \(f\) while the reconstruction algorithm is optimised by parameters learned in \(g\) over the learning dataset. The acquisition module produces two acquired images from \(5 \times 5\) sub-aperture images of the HDR light field utilising the two optimised aperture patterns.

### 2.2 4D forward Discrete Cosine Transform on the Acquired Images

Block sizes of \(8 \times 8 \times 8 \times 8\) are partitioned in the image component. The 2D acquired images are interpreted as a 4D volume. 1D DCT in (6) is applied to all the four dimensions of the volume [Diabaja, 2019] as DCT has good decorrelation properties and is less computationally complex [Dimililer, 2022]. The 4D block are transformed from spatial to frequency domain such that the energy is concentrated around the DC coefficients.

\[
X_k = \sqrt{\frac{2}{Nc_k}} \sum_{n=0}^{N-1} x_n \cos \left( \frac{(2n + 1)k\pi}{2N} \right)
\]

\[c_k = \begin{cases} 
1/\sqrt{2} & \text{if } k = 0 \\
1 & \text{otherwise}
\end{cases}
\]

A quantization matrix is applied on the coefficients as denoted in (7), where \(X(k)\) is the DCT coefficient block, \(Q\) is the quantization matrix, \(X_q(k)\) is the quantized DCT coefficient block and \(k\) is the coefficient index. Uniform quantization is enforced by dividing the coefficients in a block with a constant value. In each 2D slice of the 4D block, the quantization scheme is applied. The quantized DC and AC coefficients are treated separately.

\[X_q(k) = \text{round} \left( \frac{X(k)}{Q(k)} \right)\]
Run-length encoding is performed to compress the AC coefficients, while Differential Pulse Code Modulation (DPCM) [Wu et al., 2015] is used for the DC coefficient. Finally, the Huffman encoder [Hu and Chang, 2000] is used to entropy encode both coefficients generating a bitstream.

\[ X(k) = X_q(k) \times Q(k) \]  

(8)

### 2.3 Uniform Colour Space Transform on DCT compressed Acquired Images

The 4D DCT compressed acquired images are transformed into perceptually uniform Intensity, Protan and Tritan (IPT) colour opponent space [Emmer and Fairchild, 1998]. The intensity information is extracted, linearly scaled [Mukherjee et al., 2018] and encoded by a Perceptual Transfer Function (PTF). An error minimising function (EMF) encode the non-linear scaled chroma information to minimise the frequently encountered quantization error. The PTF is designed following recommendations of REC 1886 [Narwaria et al., 2015] taking into account three intensity ranges (low, mid and high intensity) such that \( f(\cdot): I' \rightarrow L \)

\[
L = \begin{cases} 
    a.I' & \text{if } I' < I_s'; \\
    b.I'^{\frac{1}{2}} + d & \text{if } I' \in [I_s', I_p'); \\
    e.\log_{10}(I') + f & \text{if } I' \in [I_p', I_h].
\end{cases}
\]  

(9)

Similarly, the inverse function, \( f^{-1}(\cdot) \) is formulated as

\[
I' = \begin{cases} 
    \frac{L}{a} & \text{if } L < L_s; \\
    \frac{(L - d)}{b} & \text{if } L \in [L_s, L_p); \\
    10^{\frac{L - f}{e}} & \text{if } L \in [L_p, L_h].
\end{cases}
\]  

(10)

The power value (\( \lambda \)) is appropriately derived so that quantization error due to discretisation is minimised when applied to the input chroma information. For a target 10-bit depth, the discretised output channel \( P_{out} \in (0, 1023) \) can be optimally obtained from input channel \( P_{in} \in (0, 1) \) using (11).

\[
P_{out} = \left\lfloor \left( P_{in} \right)^{\lambda} \cdot \left( 2^n - 1 \right) \right\rfloor
\]  

(11)

The power function \( \lambda \) is computed as shown in (12), where \( M, N \) are the horizontal and vertical resolution of the frame respectively.

\[
\arg\min_{\lambda} \left( \sum_{j=1}^{M} \sum_{i=1}^{N} \left( \left( \left( P_{in} \right)^{\lambda} \cdot \left( 2^n - 1 \right) \right)^{\frac{1}{2}} - P_{in} \right) \right)
\]  

(12)

Metadata containing crucial information like scaling data, maximum and minimum chroma values, etc. are generated for each frame by the proposed scheme and stored as a lookup table (LUT). The final bitstream is encoded using HEVC.

### 2.4 Reconstruction of HDR Light Field from Decoded 4DDCT-UCS Acquired Images

The 4ddct-ucS acquired images are decoded from the primary bitstream and the secondary metadata stream. The auto-encoder network shown in Fig. 2 is used to reconstruct the HDR light field from the decompressed acquired images. Hence, we achieve a complete scheme capable of efficient representation and compression of HDR light field.

### 3 Results and Analysis

Evaluation of the proposed pipeline 4DDCT-UCS is conducted on a super-dense HDR light field ‘Super Dense Teddy’ [Gul et al., 2020] dataset having an angular resolution of 50 × 50 views and spatial resolution of 5168 × 3448 pixels. The proposed scheme was implemented on a single high-end HP OMEN X 15-DG0018TX system with 9th Gen i7-9750H, 16 GB RAM, RTX 2080 8 GB Graphics, and Windows 10 operating system. Sample sets of 64 × 64 pixels 2D image blocks are extracted from the same location of the light field datasets for training the network for 20 epochs with a batch size of 15.

The distortion parameter ‘\( d \)’ gives us the option of high compressibility or high quality of the data. The acquired images are compressed with varying distortion levels starting from \( d = 1 \) to \( d = 5 \). The overall bitstream is encoded by HEVC. The profile used is Main10 [Stöm et al., 2016] which is designed for encoding streams of 10-bit depth and 4:2:0 chroma subsampling [Hamidouche et al., 2022]. The quantization parameters (QP) is set as 2, 12, 22, 32, 42 covering most of the HEVC compression range. The decoding and reconstruction of the HDR light field are also performed.
3.1 Comparative Analysis

The performance of the proposed scheme 4DDCT-UCS is compared with JPEG-XL [Alakuijala et al., 2020] and UCS [Mukherjee et al., 2018]. In Fig. 3a, the analysis of the comparison in terms of rate-distortion is depicted. We observe from the plot that our proposed scheme exhibits high fidelity compression with a lower bit rate as compared to JPEG-XL and UCS. Since the number of input images in our proposed processing pipeline is only two, the total bytes is very low compared to the other two algorithms as shown in Fig. 3b. The reconstructed images, along with their difference from the ground truth, are presented in the Fig. 4. Further, an objective assessment using Bjontegaard metric to compare bitrate reduction of proposed scheme with respect to JPEG-XL codec and UCS is performed. For the chosen distortion level $d$, the average percent difference in rate change is estimated over a range of quantization parameters. Table 1 depicts comparative BD-PSNR and BD-Rate. Thus, the proposed scheme can reconstruct the light field from just two acquired images with a minor deviation from the original light field.

4 Conclusion

A novel representation and perceptual coding scheme for HDR light field based on convolutional autoencoders and 4D-DCT are presented in this paper. The proposed scheme exhibits adaptable bit rate support which is crucial for adjusting compression levels and quality according to the available bandwidth. It also provides an end-to-end framework, where it can capture and reconstruct the light field back. The proposed algorithm outperforms the state-of-the-art coder
Table 1: Bjontegaard percentage rate savings for the proposed compression Scheme (4DDCT-UCS) with respect to JPEG-XL and UCS on Super Dense Teddy HDR light field.

| Distortion(d) | JPEG-XL | UCS |
|---------------|---------|-----|
|               | BD-Rate | BD-PSNR | BD-Rate | BD-PSNR |
| 1             | -86.201 | 27.668 | 193.58 | -10.326 |
| 2             | -88.119 | 36.119 | 119.51 | -7.5537 |
| 3             | -96.058 | 61.3 | -21.767 | 3.9596 |
| 4             | -94.651 | 66.725 | -24.748 | 5.1009 |
| 5             | -96.852 | 83.711 | -35.6 | 4.9842 |

JPEG-XL and UCS. In future work, we aim to incorporate a deep-learning based perceptual transfer function into the algorithm. We also aim to verify our simulated results on a light field display.

References

Hayato Watanabe, Naoto Okaichi, Takuya Omura, Masanori Kano, Hisayuki Sasaki, and Masahiro Kawakita. Aktina vision: Full-parallax three-dimensional display with 100 million light rays. *Scientific reports*, 9(1):1–9, 2019.

Ashok Veeraraghavan, Ramesh Raskar, Amit Agrawal, Ankit Mohan, and Jack Tumblin. Dappled photography: Mask enhanced cameras for heterodyned light fields and coded aperture refocusing. *ACM Trans. Graph.*, 26(3):69, 2007.

Yasutaka Inagaki, Yuto Kobayashi, Keita Takahashi, Toshiaki Fujii, and Hajime Nagahara. Learning to capture light fields through a coded aperture camera. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 418–434, 2018.

Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the 25th international conference on Machine learning*, pages 1096–1103, 2008.

Drahomir Dlabaja. 4d-dct based light field image compression. *Image*, 28(1):128, 2019.

Gihwan Lee and Yoonsik Choe. Fast and efficient union of sparse orthonormal transforms via dct and bayesian optimization. *Applied Sciences*, 12(5):2421, 2022.

Fritz Ebner and Mark D Fairchild. Development and testing of a color space (ipt) with improved hue uniformity. In *Color and imaging conference*, volume 1998, pages 8–13. Society for Imaging Science and Technology, 1998.

Gary J Sullivan, Jens-Rainer Ohm, Woo-Jin Han, and Thomas Wiegand. Overview of the high efficiency video coding (hevc) standard. *IEEE Transactions on circuits and systems for video technology*, 22(12):1649–1668, 2012.

Jyrki Alakuijala, Sami Boukortt, Touradj Ebrahimi, Evgenii Kliuchnikov, Jon Sneyers, Evgeniy Upenik, Lode Vandevenne, Luca Versari, and Jan Wassenberg. Benchmarking jpeg xl image compression. In *Optics, Photonics and Digital Technologies for Imaging Applications VI*, volume 11353, page 113530X. International Society for Optics and Photonics, 2020.

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.

Seiya Tokui, Kenta Oono, Shohei Hido, and Justin Clayton. Chainer: a next-generation open source framework for deep learning. In *Proceedings of workshop on machine learning systems (LearningSys) in the twenty-ninth annual conference on neural information processing systems (NIPS)*, volume 5, pages 1–6, 2015.

Kamil Dimililer. Dct-based medical image compression using machine learning. *Signal, Image and Video Processing*, 16(1):55–62, 2022.

Jiaji Wu, Wanqiu Kong, Jarno Mielikainen, and Bormin Huang. Lossless compression of hyperspectral imagery via clustered differential pulse code modulation with removal of local spectral outliers. *IEEE Signal Processing Letters*, 22(12):2194–2198, 2015.

Yu-Chen Hu and Chin-Chen Chang. A new lossless compression scheme based on huffman coding scheme for image compression. *Signal Processing: Image Communication*, 16(4):367–372, 2000.

Ratnajit Mukherjee, Kurt Debattista, Thomas-Bashford Rogers, Maximino Bessa, and Alan Chalmers. Uniform color space-based high dynamic range video compression. *IEEE Transactions on Circuits and Systems for Video Technology*, 29(7):2055–2066, 2018.
Manish Narwaria, Rafal Mantiuk, Mattheiu P Da Silva, and Patrick Le Callet. Hdr-vdp-2.2: a calibrated method for objective quality prediction of high-dynamic range and standard images. Journal of Electronic Imaging, 24(1): 010501, 2015.

M Shahzeb Khan Gul, Thorsten Wolf, Michel Bätz, Matthias Ziegler, and Joachim Keinert. A high-resolution high dynamic range light-field dataset with an application to view synthesis and tone-mapping. In 2020 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), pages 1–6. IEEE, 2020.

Jacob Ström, Kenneth Andersson, Martin Pettersson, Per Hermansson, Jonatan Samuelsson, Andrew Segall, Jie Zhao, Seung-Hwan Kim, Kiran Misra, Alexis Michael Tourapis, et al. High quality hdr video compression using hevc main 10 profile. In 2016 Picture Coding Symposium (PCS), pages 1–5. IEEE, 2016.

Wassim Hamidouche, Thibaud Biatek, Mohsen Abdoli, Edouard Francois, Fernando Pescador, Milos Radosavljevic, Daniel Menard, and Mickael Rault. Versatile video coding standard: A review from coding tools to consumers deployment. IEEE Consumer Electronics Magazine, 2022.

Gisle Bjontegaard. Calculation of average psnr differences between rd-curves. VCEG-M33, 2001.