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How color profile affects the visual quality in light field rendering and novel view synthesis

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Abstract
This paper investigates the impact of image color profile on the visual quality in light field rendering. Light field rendering methods require several input views, capturing the same scene from different camera positions. These views can be captured in real life by cameras or rendered from synthetic 3D scenes. A novel view can be synthesized from the input views, capturing the scene from a virtual camera position. Modern cinematography makes use of various color profiles that affect how the measured light on the camera sensor is translated into the color values of the digital image. Different profiles can be used for different purposes, be it artistic or pragmatic to reveal necessary details. The main scientific question of this paper is if certain color profiles can lead to better quality of the novel view synthesis in light field rendering. The paper shows that logarithmic profiles can significantly improve the visual quality. Three light field rendering methods from different categories were used to compare 17 widely used color profiles. Additional measurements show that post processing and color grading needs to be applied at the very end of the rendering pipeline to ensure the best quality. Also, the effect of denoising algorithms on light field rendering is measured.

Keywords Light field · Image-based rendering · Color profile · Computational photography

1 Introduction

Light field rendering methods are designed to produce a novel view captured by a virtual camera. The input data is a set of input images capturing the scene from different positions. These methods fall into the category of image-based rendering, where novel views are ren-

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dered only from input images, without prior information about the scene geometry. The input images for light field rendering usually capture the scene from different positions with capturing cameras stacked in a planar grid. The capturing can be performed with real cameras or in a 3D rendering software.

The modern film and photography industry makes use of color profiles [38]. When the incoming light from the real world, or the estimated light with path tracing in 3D rendering, enters the camera sensor, it has to be translated into a color value. This value is then stored in the given pixel of the captured image. Linear translation from the range of the captured intensity to the range of the possible color values might not be ideal. Different functions can be applied to the light intensity values so that, for example, a logarithmic translation would result in more samples in the middle of the output color range. This would eliminate over- or underexposed parts in the scene where only extreme color values are present. Each camera manufacturer includes several color profiles in their professional devices. 3D rendering software also offers several profiles for the rendered output.

The main scientific contribution of this paper is an experimental comparison of widely used color profiles in light field rendering algorithms. Three light field rendering methods are used to produce novel views from the same scenes rendered in different color profiles. The visual quality of the results is then compared. Figure 1 shows the main idea of this paper. The results obtained prove the hypothesis that different color profiles than the standard linear sRGB can improve the visual quality of the novel views in light field rendering. The main principle of light field rendering methods is matching of similar areas between the input images which estimates the geometry of the scene and leads to the synthesis of the novel view. The hypothesis is based on the assumption that certain color profiles reveal more details in very dark or light areas in the image and better spread the color values across the range, which is beneficial for the color matching algorithm. An experimental evaluation, as conducted in this paper, is necessary to confirm this hypothesis, as the extreme color values are mitigated and the amount of information needed for the successful matching might be decreased after discretization of the image into 8-bit RGB matrix. The findings presented in this paper are important for the capturing process of light fields. They can also help in the design of novel light field rendering methods which would expect certain color profile data. They suggest that when rendering a synthetic scene or capturing a real-world scene with a camera, a properly selected color profile can improve the usability of the resulting light field for novel view synthesis. The novel view then can be post-processed by color-grading methods. The main scientific contributions are as follows:

- Comparison of 17 widely used color profiles for light field rendering purposes. Logarithmic profiles can significantly improve the visual quality of rendered results, with CanonLog3 being the best option.

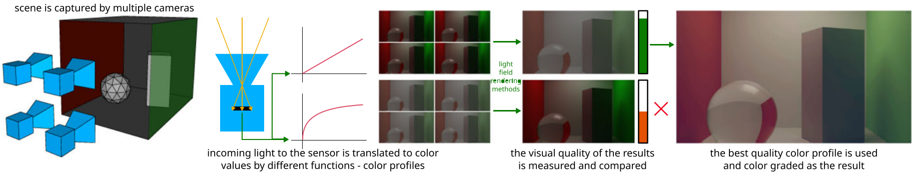


Fig. 1 The scene is captured by several cameras. The captured images are stored with different color profiles based on the different functions used for the light intensity to color conversion. The data of different profiles are used in light field rendering, and the visual quality of the results is measured

- Measurement of the effect of the denoising algorithms on light field rendering. The results show that methods based on focus map and per-pixel computations can gain a quality boost with denoised input views.
- Measurement of the color grading process and its effect on the visual quality in light field rendering. The results show that the color grading needs to be placed at the end of the rendering pipeline to achieve the best quality.

2 Related work

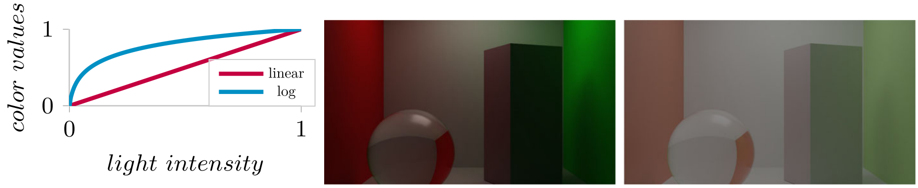
Light propagation in a given scene can be described by a 7D plenoptic function $Li = L(\mathbf{p}, \mathbf{d}, m, \lambda)$. Light intensity Li is the result, often represented as an 8-bit RGB color vector in computer graphics when the wavelength λ is omitted. The observation point with 3D coordinates $\mathbf{p}$ and a 2D direction vector $\mathbf{d}$ define the incoming light ray at a given time moment m [3]. The light in the real world is continuous. Such measures are difficult to represent in computers. In practice, the light field is often defined for a given subset of space and a limited range of possible viewing positions and angles [11]. The function is approximated by a discrete representation consisting of a set of images that capture the scene from different camera positions [21]. The cameras are often stacked on a planar 2D grid. Light field data can be rendered from synthetic scenes or captured by camera in the real world, and many datasets exist [15, 34, 42, 49]. Light field related studies with a methodology similar to this paper were also conducted to compare different compression methods [2, 36, 43], HDR image reconstruction [13], quality assessment [27, 28], etc.

2.1 Light field rendering

Image-based rendering principles are used to produce novel views from the input light field images. The methods internally estimate structural information about the scene and then synthesize a novel view, which can be positioned between the input views. Methods based on focus map estimation [5] are capable of producing high-quality novel views in real time on GPU. These methods compute many differently focused novel images of the scene and then determine which focusing distance is the optimal one for the given pixel. This information is stored in a focus map that visually resembles a depth or disparity map. The focus map is then used to guide the rendering of the result. Similar principle of the 3D cost volume [12] is used in an approach [20] where tens of differently focused views are generated and then the sharp segments are detected. The novel image is then composed of these segments.

Another way to render novel views is to use optical flow. Optical flow is the result of the method that searches for the best match of pixel blocks in two input images. The optical flow motion vectors represent the amount of displacement of the given pixel block from one image to the other. NVIDIA FRUC [9] uses optical flow to interprolate novel views between existing images on GPU.

Deep learning methods can also be used to produce novel views. Standard NERF methods such as Instant NGP [29] can synthesize virtual views from a set of images of the same scene. However, these methods often fail with the light field data that lack free-look images from many different perspectives. Frame interpolation methods [19, 30, 31, 33] can be used twice to generate intermediate views between the four closest input frames and then to produce the final view of the intermediate ones.



(a) color profile charts (b) linear image (c) log image

Fig. 2 The input light on the camera sensor can be translated into image color values linearly or according to a defined function. Linear translation to the output color range distributes the light across the range. Logarithmic translation mitigates too bright or too dark areas and reveals more details in the scene but makes the image look dull

2.2 Color profiles

Any capturing device like a camcorder or camera has a specific representation of the captured image. Reproducing the colors accurately using such devices is a complex problem [18]. The internal color space of the capturing device depends on its technical specifications. Color management techniques are then used to transform the captured colors to the expected color space of the output device, such as a TV, projector, or PC monitor [39]. The goal is to make the image look the same on all viewing output devices. The transformation of the image is performed by applying a color profile. Profiles are often simulated in software, following the hardware specifications of the desired device [32]. Each device supports a different color gamut, which defines the range of the available colors. The goal of modern output and input devices is to support a wide gamut to accurately reproduce the original colors of the real world and to offer more freedom to post-processing and color-grading methods [45]. Look-up-table (LUT) is often used to match the colors of the input device with the output device [40, 47]. Various color profiles, such as ACES [1], ACEScc [25], ARRI K1S1 [7], RED IPP2[1], T-CAM v2 or T-Log[2], are often used to adjust the colors of the captured video or still images to reach specific artistic intentions and enhance the color-grading process. Blender[3] modeling software implemented a new AgX profile for wide gamut and spectral rendering. Similarly, popular video editing software DaVinci Resolve uses a custom wide-gamut color profile called Intermediate. Logarithmic profiles [14] are used to capture the most information without excessive storage requirements. Such profiles use a logarithmic conversion of the input luminance to colors, so that details are visible in very dark or bright parts of the image; see Fig. 2. The format of the profiles is defined by International Color Consortium (ICC) [37].

The visual accuracy or artistic post processing are not the only reasons why color profiles are widely used. Certain types of data, such as astronomical [35] or from biosensors [48], would be difficult to analyze without color space transformation. According to this paper, color profiles can affect optical-flow-based algorithms [24]. This might also be relevant for other than light field usages, for example, instance segmentation in videos [46], where transforms regarding colors or the geometry of the images can significantly affect the resulting quality [44]. Various vision methods, such as automatic lane detection, preprocess the input video frames for denoising purposes [23]. Color filters in different color spaces than RGB like LAB, LUV, or HSL can be applied. Note that different color spaces, such as YUV and

1 red.com/red-tech/image-processing-pipeline-ipp2

2 filmlight.ltd.uk/support/customer-login/colourspaces/colourspaces.php

3 blender.org

LAB, were already tested for computations of the correspondences between the input images in light field rendering [4]. However, color profiles, as discussed in this paper, have not yet been investigated.

3 Experiments

Luminance is a continuous measure describing the light intensity in the real world and is converted to a digital representation in the camera. The sensor converts the incoming luminance to a voltage which can be interpreted as a discrete numerical color value, based on the technology and color profile used. 3D modeling software Blender is used in the experiments to simulate this scenario. Blender Cycles rendering engine uses path tracing to compute the global illumination of the scene and stores the obtained light information as an RGB floating point value per pixel. The resulting rendered float image is then usually stored as 8 or 16-bit RGB pixel matrix, which is analogous to the camera light conversion. It can be assumed that the precision of such a process is a good approximation, which makes the measured results relevant also for real scenes. The reversed order of the operations, i.e. conversion of rendered 8-bit images into a different color profile, would introduce high inaccuracy due to the already discretized and reduced amount of data at the input. 8-bit RGB images are used in the experiments, as they represent the standard format of light field datasets. This format is used since light field memory requirements are high and most of the existing methods support only 8-bit inputs. One of the disadvantages of light fields is their memory space requirements. Therefore, 10 or 16-bit data are not commonly used.

Standard PSNR, SSIM, and VMAF metrics are used to measure the visual quality of the result compared to a reference view. Additional no-reference metric NIQSV+ [41] for multi-view image synthesis evaluation was used for further analysis of the results. The input light field data in different color profiles are used in three light field rendering methods: Per-Pixel [5] belonging to the focus map category, IFRNet [19] belonging to the deep learning category, and FRUC [9] belonging to the optical flow category. The purpose of the experiments is not to compare the selected methods. They are used to cover all major existing categories of light field rendering. Per-Pixel method computes the disparity between the input images and identifies the optimal focusing value for each pixel. IFRNet interpolates the novel image based on the pre-trained model, which is designed to produce intermediate frames between similar images. FRUC uses the widely used optical flow computation that estimates the motion between consecutive frames and performs the interpolation based on this motion field. These three methods use different approaches to produce a novel view and were selected to make the results generally acceptable. All are designed to accept standard gamma-corrected inputs. Therefore, a different color profile can significantly affect the output. Note that the selected color profile does not affect the time performance or memory requirements of the methods.

3.1 Color profile

Selection of the best color profile for light field rendering is the main task of this experiment. The best color profile means that the input data in such a profile would result in the best visual quality of the novel interpolated view. Light field rendering methods introduce artifacts in their results. The goal of this experiment is to find out which color profile leads to the least number of such artifacts. Figure 3 shows the measurement process used in this experiment. The input images are rendered in Blender with different color profiles and then used in the

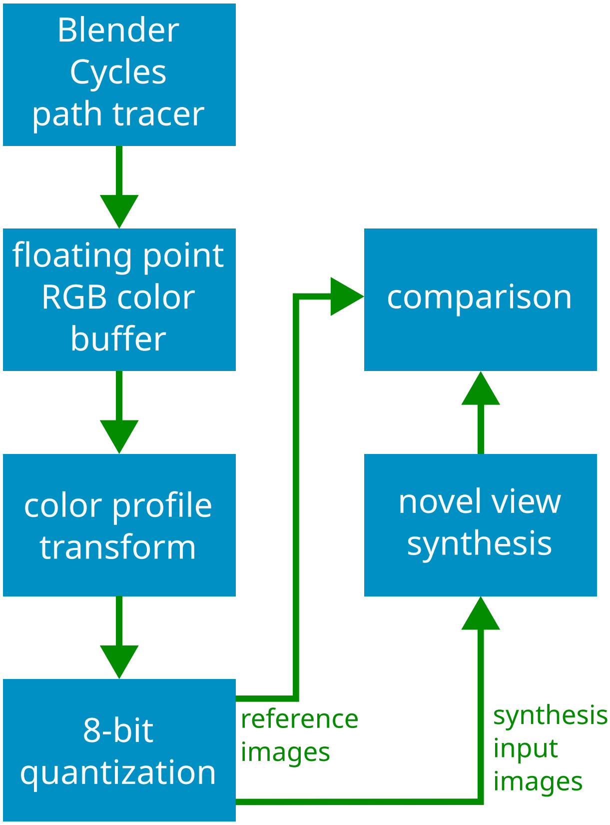


Fig. 3 The conducted measurement process is described in the figure. 3D scene is rendered and transformed into the selected color profile. The rendered data are split to reference and input images. Input images are used to synthesize a novel view using light field rendering methods and compared to the reference

light field rendering methods to produce a novel view. The amount of artifacts in the novel view is measured by the visual quality metrics.

The profiles, listed in Table 1, are selected for the measurements as the most widely used ones in cameras and in 3D rendering. Other profiles were also considered and experimented with in the initial stages of this investigation. The final selection reflects the popularity of the profiles and also their properties. Other profiles considered, such as OpenDRT, JzDT, ARRI ALF2, AgX Kraken, Log3G10, BMDFilm Gen5, etc., showed similar or worse results than those selected and were not included. The selection contains 7 non-logarithmic and 10 logarithmic profiles. The number of logarithmic profiles is a little higher to cover all the widely used ones, as this category shows better results.

3.2 Denoising

Previous works regarding focus-map-based methods [5], such as Per-Pixel [5], revealed that video compression on the input light field images does not only help with the excessive light field rendering memory requirements, but can also enhance the visual quality of the result. This is caused by the inherent characteristic of the video compression. The inter-

Table 1 The table contains a list of the measured color profiles

profile	description
none	linear conversion of colors
standard	classic gamma correction in sRGB
ACES	film industry standard profile
T-CAM-v2	by FilmLight company
AgX	preferred profile in Blender
ARRI-K1S1	by ARRI company
RED-IPP2	used in RED cameras
ACEScc-Log	improved ACES for log scale
T-Log	by FilmLight company
AgX-Log	AgX with log transform
Davinci-Log	Intermediate profile in Davinci Resolve
V-Log	used in Panasonic cameras
S-Log	used in Sony cameras
N-Log	used in Nikon cameras
F-Log	used in Fujifilm cameras
CanonLog3	used in Canon cameras
ProTune-Log	used in GoPro cameras
Apple-Log	used in Apple devices

frame compression reduces the data by eliminating redundancy between the images. Very similar areas of the image can be viewed as nearly-same and their difference between the images might be mitigated. The result of this process is similar to denoising where unique noise in the image is suppressed and the pixel-scale details are mitigated.

The main question of this experiment is if denoising based on one view can be used in the same way as the inter-view denoising mentioned earlier to improve the quality of the rendered result in light field rendering. Three types of data are used in this experiment as the input of light field rendering methods. The first type is a rendered scene without any denoising, but using a high number (1024) of path-tracing samples to mitigate the noise by oversampling. The second type is the same but with only 16 samples, which leads to a noisy result. However, this result is denoised by Open Image Denoising [8] which uses information gained by the rendering passes to remove the noise and performs a 3D denoising. The third type uses the images of the first type but filtered by a 2D denoising algorithm High Quality DeNoise 3D[4]. The rendered results are compared to find out how the rendered image quality changes based on these three types of input. The results are compared to the references from the given noise-level category. The error introduced by the noise or denoising alone is intentionally not measured to evaluate the methods and their sensitivity to the noise.

3.3 Post processing

Captured scenes are often necessary to edit with color-grading methods. Especially logarithmic color profiles look dull and are not intended to be used directly without post processing. Standard light field datasets contain grids of at least 8×8 images in size. Editing the input

[4] github.com/Asd-g/AviSynth-hqdn3d

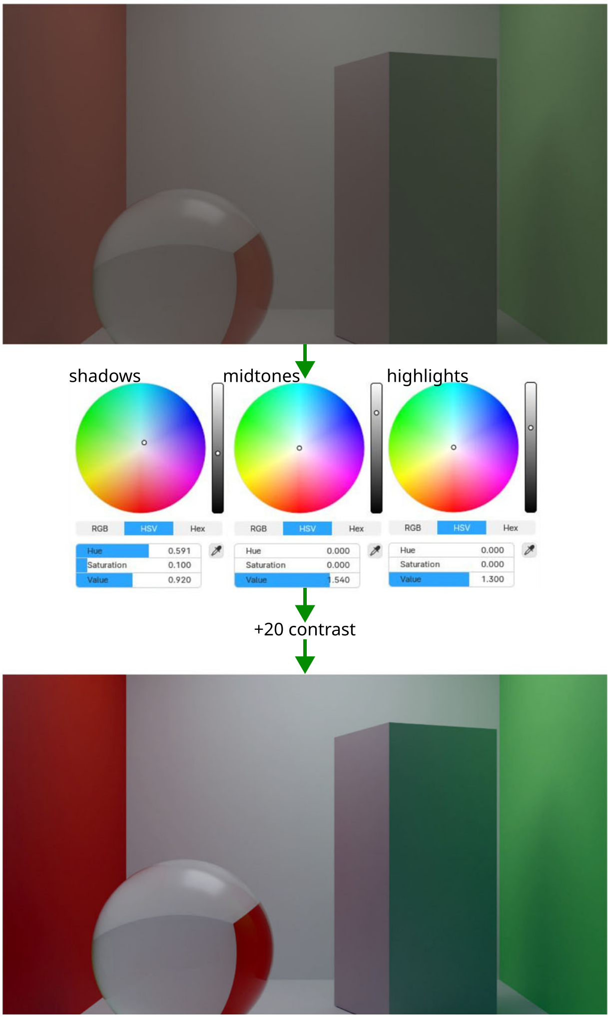
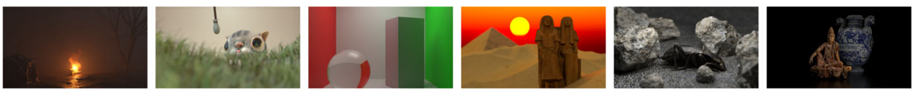


Fig. 4 The logarithmic input image is color graded to make it visually appealing. The color grading operations depicted in the figure are used in the experiment

images would result in 64 color-grading operations. Standard light field use cases expect the synthesis of thousands of novel views, for example, when the scene is viewed with a moving virtual camera in interactive frames per second such as commonly used 24–60 fps. The constant application of color grading to the input images instead of application each time the novel view is synthesized could result in a significantly smaller number of color grading



(a) *bonfire* (b) *cat* (c) *Cornell box* (d) *low frequency* (e) *macro* (f) *simple setting*

Fig. 5 The central views of the used light field dataset are presented in the figure

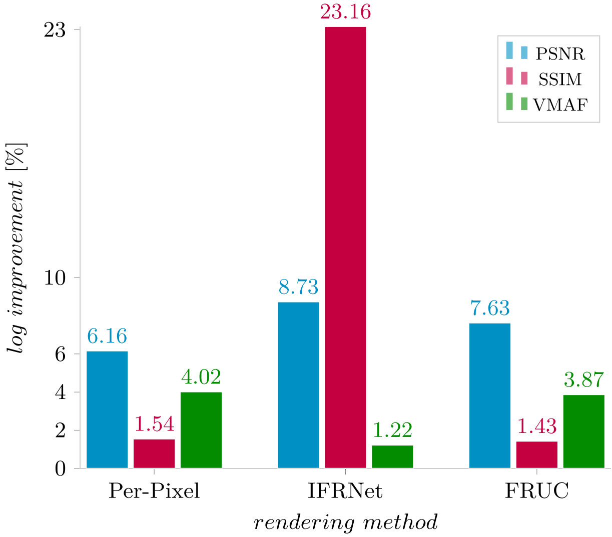


Fig. 6 The figure shows how log-based color profiles outperform non-logarithmic ones in quality metric percentual improvement

operations. This experiment aims to find out whether application of color grading before the synthesis would affect the visual quality of the result and if this application is suitable or not. Figure 4 shows how the input images are adjusted for the experiment. Only standard color grading methods were applied: color balance with highlighting of the dark and light parts with slight addition of blue tint to the shadows and increase of the global contrast.

4 Results & discussion

All experiments are executed on a machine equipped with Nvidia GeForce RTX 2070 GPU and Intel(R) Core(TM) i5-8500 CPU @ 3.00GHz CPU, running Arch Linux. The light fields used in the experiment, shown in Fig. 5, are taken from the existing dataset [6] as Blender projects.

Measuring 17 profiles with 3 methods on 6 scenes resulted in 306 tests in total. The scenes were selected to cover the usual use cases and represent different categories of imagery to avoid bias caused by the same kind of input data. *Bonfire* represents a low-light setting with one bright object. *Cat* represents a neutral photo with standard lighting conditions and visible depth of field. *Cornell box* is a standard benchmarking scene with different colors, single-colored areas, and a glassy material, which might be difficult to handle by interpolation algorithms. *Low frequency* is a scene with a wide depth range that causes greater disparity values and challenges interpolation algorithms. *Macro* is a classic example of a close-up photo with a mild depth of field. *Simple setting* represents a prepared scene with static background and a well-lit object of interest. The color palettes and brightness levels also vary across the dataset used.

The color profiles used are added to Blender from the PixelManager repository.[5]

[5] github.com/Joegenco/PixelManager

4.1 Color profile

The measurements show that logarithmic color profiles reveal more details in the scene that can be used for the color matching in light field rendering. Figure 6 shows the percentual improvement of logarithmic color profiles. The color metrics are measured on all scenes and the average of the logarithmic over non-logarithmic profiles is computed. Logarithmic profiles bring an improvement to all rendering methods.

All color profiles are compared to the profile where no transform is applied – the colors are converted in a linear manner. Figure 7 shows that non-logarithmic profiles perform worse than the basic color conversion. Their visual quality change in percents is mostly negative. Logarithmic profiles show the most significant improvement. Based on the average of the metrics, CanonLog3, N-Log, S-log, and T-log perform the best, with CanonLog3 showing the highest overall visual quality. CanonLog3 also shows the highest NIQSV+ score among the log profiles.

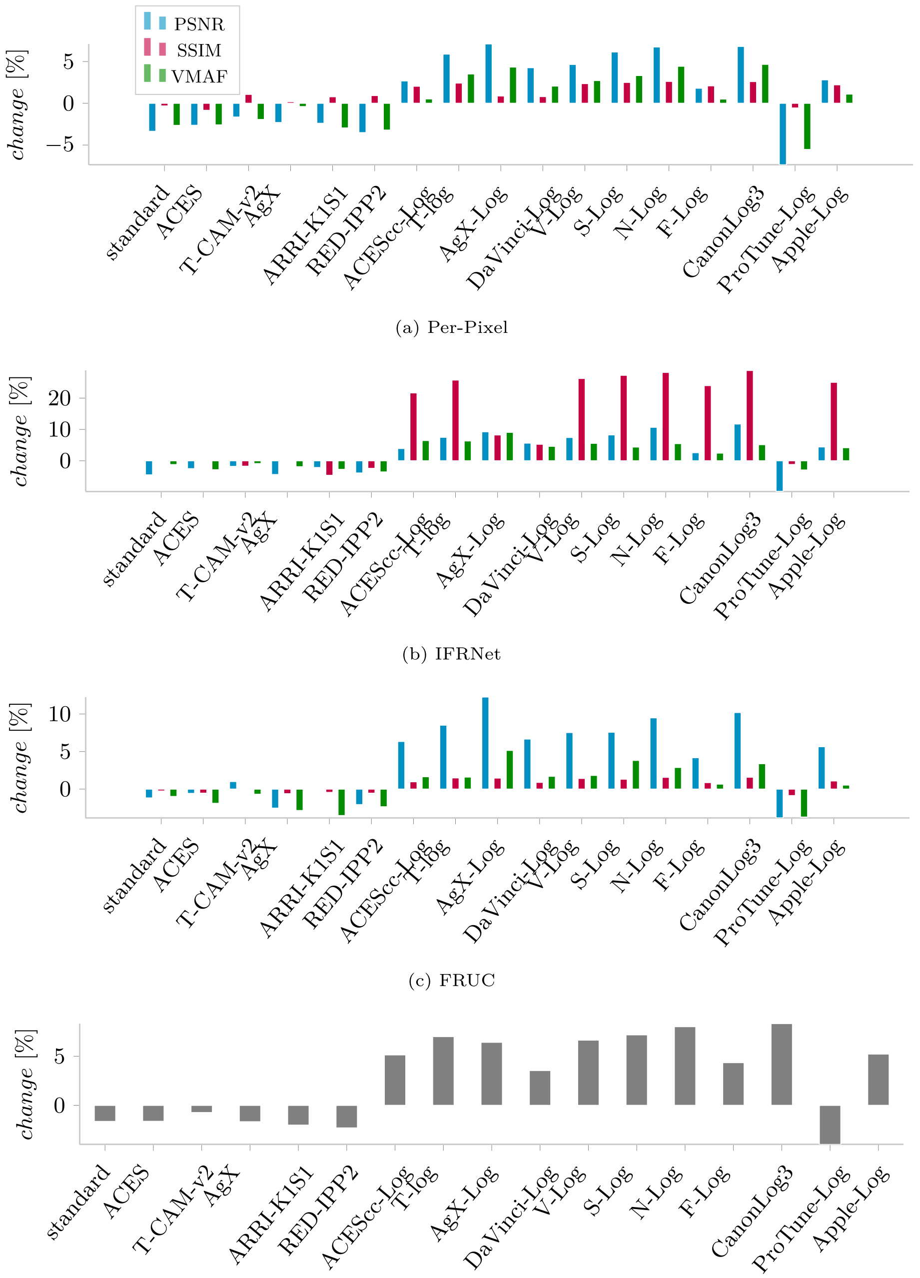
Figure 8 shows a visual comparison of the results. The interpolation artifacts are less significant in the case of logarithmic data.

The *simple setting* scene shows the best average improvement of 15% when using logarithmic profiles compared to non-log ones. It can be caused by many dark areas that are enhanced by the logarithmic color scale. The lowest improvement, about 1%, is with the *Cornell box* scene. The scene does not contain extreme lighting conditions, which makes it less prone to the disappearance of details in such areas. This shows that light field rendering algorithms can perform better with logarithmic color profiles, such as CanonLog3, when the lighting of the scene is low.

There are several possible reasons why logarithmic profiles improve interpolation quality. The interpolation methods internally look for similar areas in the input images to estimate the disparity or geometry of the scene. The profiles reveal details that would otherwise not be visible. This alone can aid in interpolation, as it can better detect details in areas that are too bright or too dark; see Fig. 9. In addition, the closer distance between the corresponding colors helps to match them. The contrast in the logarithmic image is visually lower and similar colors do not have such a large distance between them. Due to the reduction of the color range, a color noise, which is almost always present in light field images, is reduced, and even noisy corresponding pixels are more likely to be matched. A similar principle was used in a denoising algorithm using non-linear image decomposition [16]. This can also be a disadvantage. The algorithms might identify incorrect colors as similar ones. Logarithmic scale can also lead to a loss of details due to quantization of the color data. However, interpolation algorithms usually sample multiple pixels within a certain neighborhood. The aggregated color can be a weighted average of multiple pixels, which increases the resolution of the color range used. These findings seem to be in accordance with similar research in which the logarithmic color profile is utilized to improve the color matching or reconstruction. For example, in color stabilization of multi-source imagery [10], saturation detail enhancement in cloud removal method for satellite images [26], or in color correction based on point cloud alignment [22]. Previous works also described the significance of the logarithmic color scale for image interpolation or color prediction [17].

4.2 Denoising

The results regarding denoising in Fig. 10 show that the denoising algorithms perform well with the Per-Pixel method, similarly to the denoising caused by video compression. However,



(a) Per-Pixel

(b) IFRNet

(c) FRUC

(d) Average of all methods and metrics

Fig. 7 The figure shows how all tested profiles perform when compared to raw linear color profile with no transforms. Scenes *macro, low frequency, and simple setting* are excluded from VMAF measurements in IFRNet due to the instability of the metric with the artifacts produced by the deep learning method

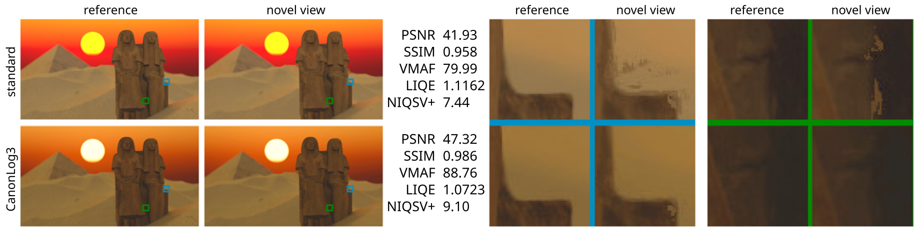
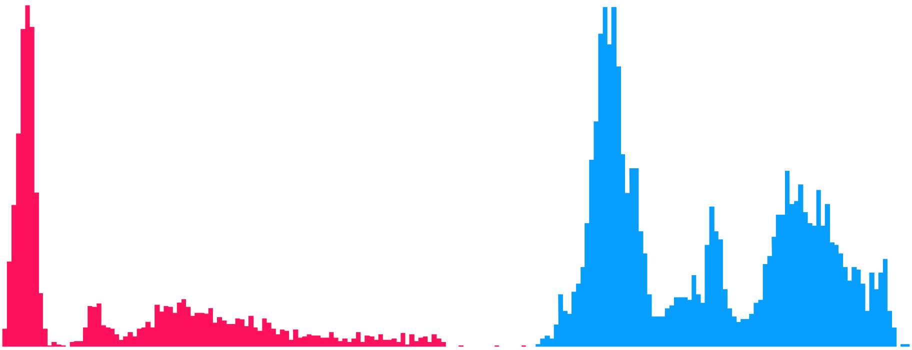


Fig. 8 *Low frequency* scene is used in Per-Pixel light field rendering method with data with standard and CanonLog3 color profiles. The figure shows how the log profile mitigates interpolation artifacts. Both results are color graded to visually match each other as much as possible

the IFRNet and FRUC methods do not improve with denoising. IFRNet seems to be invariant to denoising. FRUC shows worse results. This shows that denoising can help to produce a better focus map in the Per-Pixel method, but deep learning and optical flow approaches do not benefit from it. NIQSV+ metric shows about 11% improvement in the denoised results on average. This also shows that denoising can be safely used, for example, for faster 3D rendering without a significant risk of worse light field rendering results. Only the optical flow approach might not work well, probably because of the denoising smoothing that causes the block matching to fail due to vanishing details in nearby blocks.

4.3 Post processing

Figure 11 shows that post processing of input data captured in a logarithmic color profile distorts the rendered result significantly. This leads to the conclusion that post processing of the image needs to be performed at the very end of the rendering pipeline on the resulting novel view. Although applying the color grading on the input data might lead to fewer operations, the visual quality loss is way too significant.



(a) *linear* (b) *logarithmic*

Fig. 9 The normalized color-intensity histograms, corresponding to images in Fig. 2, show that a logarithmic color space reveals more color details in the middle of the color range and eliminates aggregation of colors at the end of the range

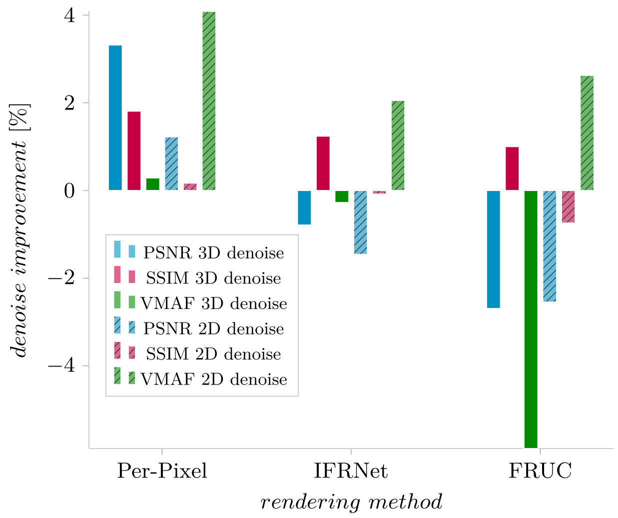


Fig. 10 The effect of denoising on the visual quality of the novel view synthesis in light field rendering is shown in the chart

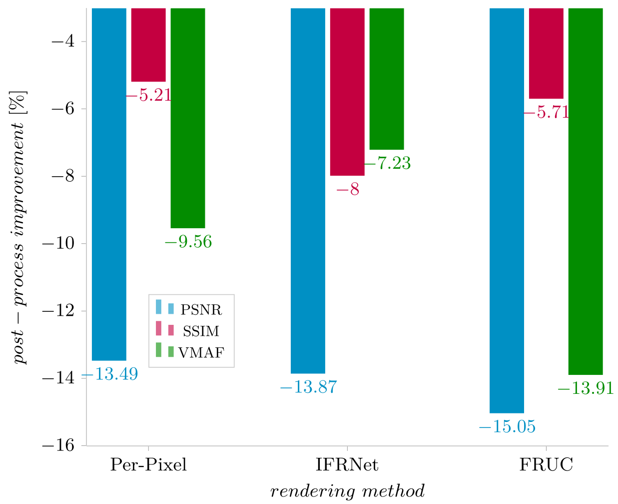


Fig. 11 The improvement is negative in all cases. Therefore, post processing of the input log data is not a viable option

5 Conclusion

This paper compared different color profiles that are currently widely used in the cinematography and photography industry. They were compared in light field rendering scenario. The input images, representing a discrete light field, were produced in different color profiles and used to render a novel view. The results of the conducted experiments showed that the logarithmic color profiles are more suitable to be the input of light field rendering methods. The visual quality of the novel views was significantly higher. CanonLog3 proved to be the best color profile to be used for a novel view synthesis in light field rendering. This does not mean that only Canon cameras that use this profile are to be used for light field acquisition. When using synthetic scenes, this profile can be simulated. When real-life scenes are captured, the profile can be applied to the raw data afterwards or a similar profile can be used during the capture. As shown in the measurements, other logarithmic profiles used in professional cameras from other companies, such as V-Log, S-Log, N-Log, or F-Log, yield a comparable improvement in quality. The logarithmic mode available in most DSLR (digital single-lens reflex camera) or mirrorless cameras would suffice.

In order to make the synthesized result visually appealing, color grading is necessary. The experimental results show that the position of the color grading process in the rendering pipeline can significantly affect the resulting quality. The color grading needs to be applied at the very end of the pipeline and not at the beginning as the user might suggest because of the lower number of necessary processing operations. Additionally, this paper revealed that denoising of the input data can also lead to better quality view synthesis in case of focus-map based light field rendering methods.

The three methods and six scenes used in the measurements were selected to cover the common and disjoint categories to avoid bias and provide general results. However, other scenes might exist that would yield better results when using different color profiles than suggested. The logarithmic profiles showed significant quality gain which still justifies their general usage. CanonLog3 might not necessarily be the best profile for all types of data. Nevertheless, the findings in this study suggest that the user can safely start capturing light fields in logarithmic profiles and select possible alternatives in this category. Various light field rendering methods can be adjusted with parameters, such as the size of disparity searching windows etc. These settings might also play a role in the interpolation, regarding color profile used. This study is limited to a general overview. It does not focus on detailed settings of specific methods, as this might be a topic for future work.

This paper provides important information for future light field rendering methods. The methods used in this paper belong to the state of the art and expect the standard sRGB input. Future methods might be specially designed to exploit the characteristics of the logarithmic color profiles, which can lead to a more convenient and optimal light field capturing and rendering process. A custom color profile, specifically designed for light field rendering might be proposed in future work. This paper serves as a good starting point for the possible light-field-friendly color profile proposal. The correct choice of a color profile might be even more crucial when working with 10-bit, 16-bit, float, or HDR data. These formats need to be investigated further and experimentally measured in the future.

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Data Availability No original datasets were produced during this study. The existing dataset used is publicly available.

Declarations

Competing interests All authors declare that they have no conflicts of interest.

References

1. Arrighetti W (2017) The academy color encoding system (aces): a professional color-management framework for production, post-production and archival of still and motion pictures. J Imaging 3(4). https://doi.org/10.3390/jimaging3040040. https://www.mdpi.com/2313-433X/3/4/40
2. Bařina D, Šolony M, Chlubna T et al (2022) Comparison of light field compression methods. Multimed Tools Appl 81(2):2517–2528. https://doi.org/10.1007/s11042-021-11645-x. https://www.fit.vut.cz/research/publication/12613
3. Bergen JR, Adelson EH (1991) The plenoptic function and the elements of early vision. Computational Models Visual Processing 1:8
4. Chlubna T, Milet T, Zemčík P (2021) Real-time per-pixel focusing method for light field rendering. Comput Vis Media 2021(7):319–333. https://doi.org/10.1007/s41095-021-0205-0. https://www.fit.vut.cz/research/publication/12429
5. Chlubna T, Milet T, Zemčík P et al (2023) Real-time light field video focusing and gpu accelerated streaming. J Signal Process Syst 95(6):703–719. https://doi.org/10.1007/s11265-023-01874-8. https://www.fit.vut.cz/research/publication/13014
6. Chlubna T, Milet T, Zemčík P (2024) Lightweight all-focused light field rendering. Comput Vis Image Underst 244:104031. https://doi.org/10.1016/j.cviu.2024.104031
7. Cooper S, Achard R, Fry A et al (2017) Aces - retrospective and enhancements. ACES. https://doi.org/10.5281/zenodo.345624
8. Corporation I (2023) Intel open image denoise - high-performance denoising library for ray tracing. https://www.openimagedenoise.org/documentation.html
9. Corporation N (2023) Nvidia optical flow engine-assisted frame rate up conversion. https://docs.nvidia.com/video-technologies/optical-flow-sdk/pdf/NVOFA_FRUC.pdf
10. Gil Rodriguez R, Vazquez-Corral J, Bertalmio M (2017) Color-matching shots from different cameras having unknown gamma or logarithmic encoding curves. pp 1–15. https://doi.org/10.5594/M001807
11. Gortler SJ, Grzeszczuk R, Szeliski R et al (1996) The lumigraph. In: Proceedings of the 23rd annual conference on computer graphics and interactive techniques. Association for Computing Machinery, New York, NY, USA, SIGGRAPH '96, p 43–54. https://doi.org/10.1145/237170.237200
12. Gu X, Fan Z, Zhu S et al (2020) Cascade cost volume for high-resolution multi-view stereo and stereo matching. In: 2020 IEEE/cvf conference on computer vision and pattern recognition (CVPR), pp 2492–2501. https://doi.org/10.1109/CVPR42600.2020.00257
13. Guindy M, Kiran AV, Kara PA et al (2021) Performance evaluation of hdr image reconstruction techniques on light field images. In: 2021 International conference on 3D immersion (IC3D), pp 1–7. https://doi.org/10.1109/IC3D53758.2021.9687182
14. Gupta SS, Banik PP, Kim KD (2019) Study on the log-encoding system for a camera image sensor. In: 2019 International conference on information and communication technology convergence (ICTC), pp 1047–1049. https://doi.org/10.1109/ICTC46691.2019.8939972
15. Honauer K, Johannsen O, Kondermann D et al (2017) A dataset and evaluation methodology for depth estimation on 4d light fields. In: Lai SH, Lepetit V, Nishino K et al (eds) Computer vision - ACCV 2016. Springer International Publishing, Cham, pp 19–34
16. Ishii Y, Saito T, Komatsu T (2007) Denoising via nonlinear image decomposition for a digital color camera. In: 2007 IEEE International conference on image processing, pp I – 309–I – 312. https://doi.org/10.1109/ICIP.2007.4378953
17. Jourlin M, Breugnot J, Itthirad F et al (2011) Chapter 2 - logarithmic image processing for color images. In: Hawkes PW (ed) Advances in imaging and electron physics, advances in imaging and electron physics, vol 168. Elsevier, p 65–107. https://doi.org/10.1016/B978-0-12-385983-9.00002-8. https://www.sciencedirect.com/science/article/pii/B9780123859839000028
18. Kirchner E, van Wijk C, van Beek H et al (2021) Exploring the limits of color accuracy in technical photography. Herit Sci 9(1):1–13. https://doi.org/10.1186/s40494-021-00536-x
19. Kong L, Jiang B, Luo D et al (2022) Ifrnet: Intermediate feature refine network for efficient frame interpolation. In: 2022 IEEE/CVF Conference on computer vision and pattern recognition (CVPR), pp 1959–1968. https://doi.org/10.1109/CVPR52688.2022.00201

20. Kubota A, Takahashi K, Aizawa K et al (2004) All-focused light field rendering. In: Keller A, Jensen HW (eds) Eurographics workshop on rendering. The Eurographics Association. https://doi.org/10.2312/EGWR/EGSR04/235-242
21. Levoy M, Hanrahan P (1996) Light field rendering. Association for Computing Machinery, New York, NY, USA, SIGGRAPH '96, p 31–42. https://doi.org/10.1145/237170.237199
22. Li B, Jiang G, Shao W (2015) Color correction based on point clouds alignment in the logarithmic rgb space. Vis Comput 31(3):257–270. https://doi.org/10.1007/s00371-013-0916-z
23. Liu D, Wang Y, Chen T et al (2019) Application of color filter adjustment and k-means clustering method in lane detection for self-driving cars. In: 2019 Third IEEE International conference on robotic computing (IRC), pp 153–158. https://doi.org/10.1109/IRC.2019.00030
24. Lu Y, Wang Q, Ma S et al (2023) Transflow: Transformer as flow learner. In: 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp 18063–18073. https://doi.org/10.1109/CVPR52729.2023.01732
25. Maltz A (2015) The academy color encoding system: Standards for digital image interchange, color management and long-term archiving. In: SMPTE 2015 Annual technical conference and exhibition, pp 1–9. https://doi.org/10.5594/M001664
26. Markchom T, Lipikorn R (2018) Thin cloud removal using local minimization and logarithm image transformation in hsi color space. In: 2018 4th International conference on frontiers of signal processing (ICFSP), pp 100–104. https://doi.org/10.1109/ICFSP.2018.8552064
27. Meng C, An P, Huang X et al (2020) Full reference light field image quality evaluation based on angular-spatial characteristic. IEEE Signal Process Lett 27:525–529. https://doi.org/10.1109/LSP.2020.2982060
28. Min X, Zhou J, Zhai G et al (2020) A metric for light field reconstruction, compression, and display quality evaluation. IEEE Trans Image Process 29:3790–3804. https://doi.org/10.1109/TIP.2020.2966081
29. Müller T, Evans A, Schied C et al (2022) Instant neural graphics primitives with a multiresolution hash encoding. ACM Trans Graph 41(4):1–15. https://doi.org/10.1145/3528223.3530127
30. Niklaus S, Liu F (2020) Softmax splatting for video frame interpolation. In: 2020 IEEE/CVF conference on computer vision and pattern recognition (CVPR). IEEE Computer Society, Los Alamitos, CA, USA, pp 5436–5445. https://doi.org/10.1109/CVPR42600.2020.00548
31. Park J, Kim J, Kim CS (2023) Biformer: Learning bilateral motion estimation via bilateral transformer for 4k video frame interpolation. In: Computer vision and pattern recognition
32. Plaisted PB, Chung R (1997) Construction features of color output device profiles. In: Color and imaging conference, society for imaging science and technology, pp 141–146
33. Reda F, Kontkanen J, Tabellion E et al (2022) Tensorflow 2 implementation of film: Frame interpolation for large motion. https://github.com/google-research/frame-interpolation
34. Rerabek M, Ebrahimi T (2016) New light field image dataset. In: 8th International conference on quality of multimedia experience (QoMEX), CONF
35. Saydjari AK, Schlafly EF, Lang D et al (2023) The dark energy camera plane survey 2 (decaps2): more sky, less bias, and better uncertainties. Astrophys J Suppl Ser 264(2):28. https://doi.org/10.3847/1538-4365/aca594
36. Schelkens P, Astola P, da Silva EAB et al (2019) JPEG Pleno light field coding technologies. In: Tescher AG, Ebrahimi T (eds) Applications of digital image processing XLII, International Society for Optics and Photonics, vol 11137. SPIE, p 111371G. https://doi.org/10.1117/12.2532049
37. Sharma A (2018) Introduction. John Wiley & Sons Ltd, chap 1:1–35. https://doi.org/10.1002/9781119223702.ch1. https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119223702.ch1
38. Sharma A (2019) Exploring the basic concepts of hdr: dynamic range, gamma curves, and wide color gamut. Inf Disp 35(5):14–18. https://doi.org/10.1002/msid.1060. https://sid.onlinelibrary.wiley.com/doi/abs/10.1002/msid.1060
39. Srivastava S, Ha T, Allebach J et al (2009) Color management using device models and look-up tables. In: Proceedings of Gjøvik color imaging symposium, pp 54–61
40. Srivastava S, Ha TH, Delp EJ et al (2009) Generating optimal look-up tables to achieve complex color space transformations. In: 2009 16th IEEE International conference on image processing (ICIP), pp 1641–1644. https://doi.org/10.1109/ICIP.2009.5413721
41. Tian S, Zhang L, Morin L et al (2018) Niqsv+: A no-reference synthesized view quality assessment metric. IEEE Trans Image Process 27(4):1652–1664. https://doi.org/10.1109/TIP.2017.2781420
42. Vaish V, Adams A (2008) The (new) stanford light field archive. Computer Graphics Laboratory, Stanford University 6(7)
43. Viola I, Řeřábek M, Ebrahimi T (2017) Comparison and evaluation of light field image coding approaches. IEEE J Sel Top Signal Process 11(7):1092–1106. https://doi.org/10.1109/JSTSP.2017.2740167
44. Wang W, Liang J, Liu D (2022) Learning equivariant segmentation with instance-unique querying. Adv Neural Inf Process Syst. https://doi.org/10.48550/arXiv.2210.00911

45. Wen Z, Zhou Z, Liu H et al (2021) Color revolution: toward ultra-wide color gamut displays. J Phys D Appl Phys 54(21):213002. https://doi.org/10.1088/1361-6463/abe43d
46. Yan L, Wang Q, Ma S et al (2023) Solve the puzzle of instance segmentation in videos: A weakly supervised framework with spatio-temporal collaboration. IEEE Trans Circuits Syst Video Technol 33(1):393–406. https://doi.org/10.1109/TCSVT.2022.3202574
47. You JY, Kwon SY, Kim JS et al (2010) The establishment of adaptive lut for digital cinema projectors based on icc profile. In: SMPTE Annual Tech Conference & Expo 2010, pp 1–8. https://doi.org/10.5594/M001397
48. Zhu P, Papadimitriou VA, van Dongen JE et al (2023) An optical aptasensor for real-time quantification of endotoxin: from ensemble to single-molecule resolution. Sci Adv 9(6):eadf5509. https://doi.org/10.1126/sciadv.adf5509
49. Ziegler M, op het Veld R, Keinert J et al (2017) Acquisition system for dense lightfield of large scenes. In: 2017 3DTV Conference: the true vision - capture, transmission and display of 3D Video (3DTV-CON), pp 1–4. https://doi.org/10.1109/3DTV.2017.8280412