# Light Field Intrinsics With a Deep Encoder-Decoder Network

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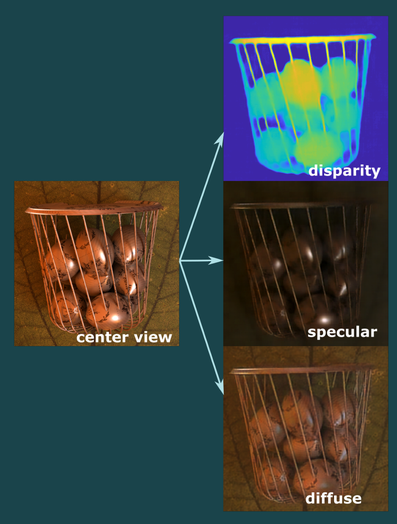
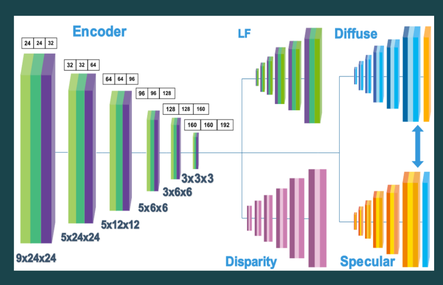
## Contributions

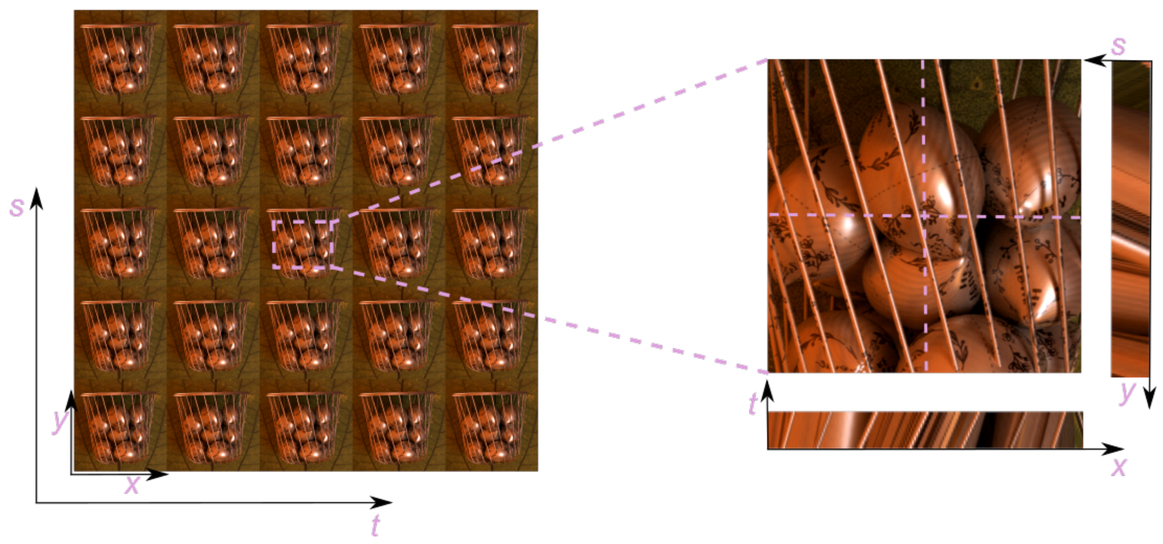
- Encoder-decoder network for disparity regression and reflection separation in light fields
- Supervised and unsupervised training
- 3D convolutions to compute features over the vertical and horizontal stack
- Synthetic light field data with ground truth intrinsic components and disparity




## Light field structure

Defined on 4D ray space $\mathcal{R} = \Pi \times \Omega$, which parametrizes rays $\boldsymbol{r} = (x, y, s, t)$ by their intersection coordinates with two planes $\Pi$ and $\Omega$, [5]. Intersection with the focal plane $\Pi$ gives view point coordinates $(s, t)$, while the image plane $\Omega$ denotes image coordinates $(x, y)$.



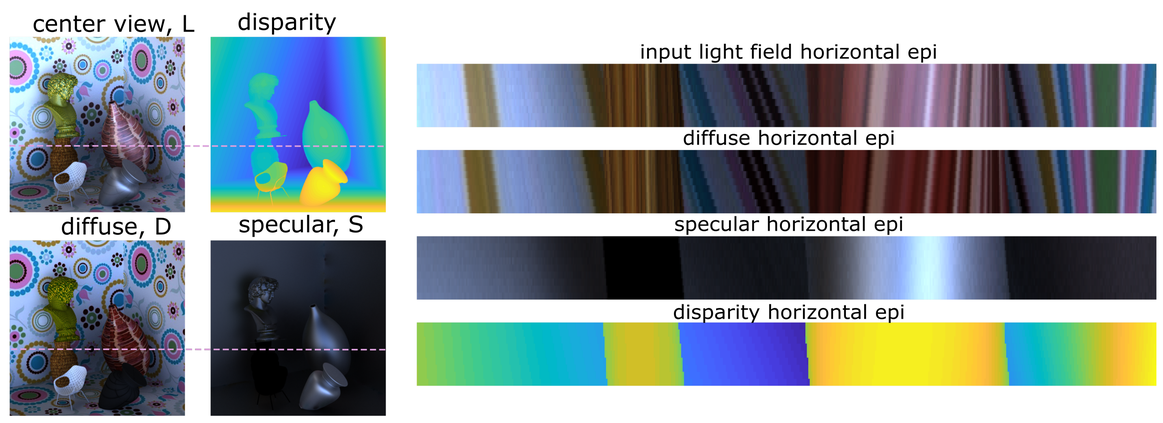

## Dichromatic model

$$L = D + S$$

The input light field $L$ can be additively separated into its diffuse and specular components $D$ and $S$, [6], [10].

**Diffuse component** and the disparity correspond to the same projections of the same 3D points and share the same pattern.

**Specular component** follows the specular flow [9], which depends on the local surface geometry and view point change.

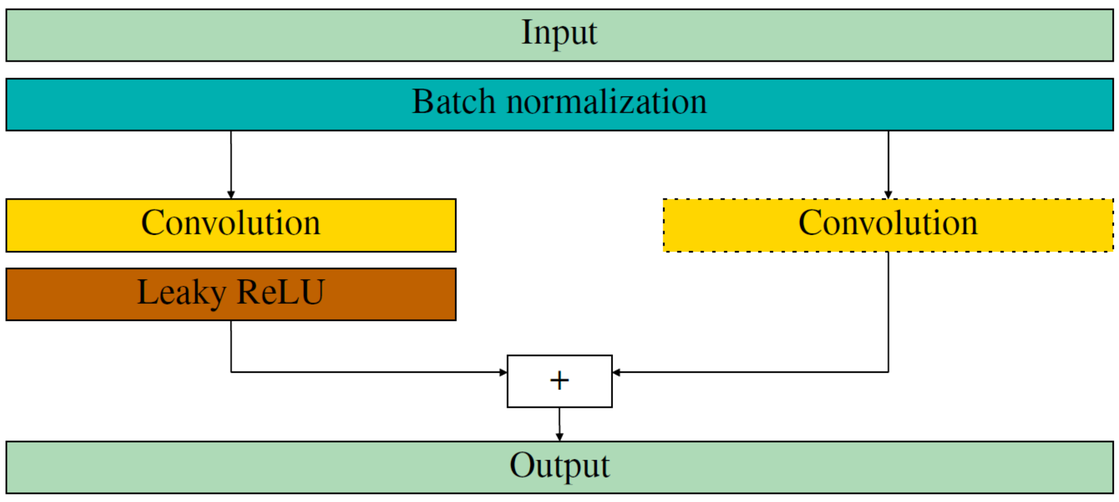



## Data


Generated based on Blender plugin provided by [2]

- 171 scenes
- 321 textures
- 109 environmental maps[3]
- 36 pre-built scenes with objects from Chocofur[1] and The British Museum[2]
- Randomized position, amount of specularity, texture and color

## Residual block

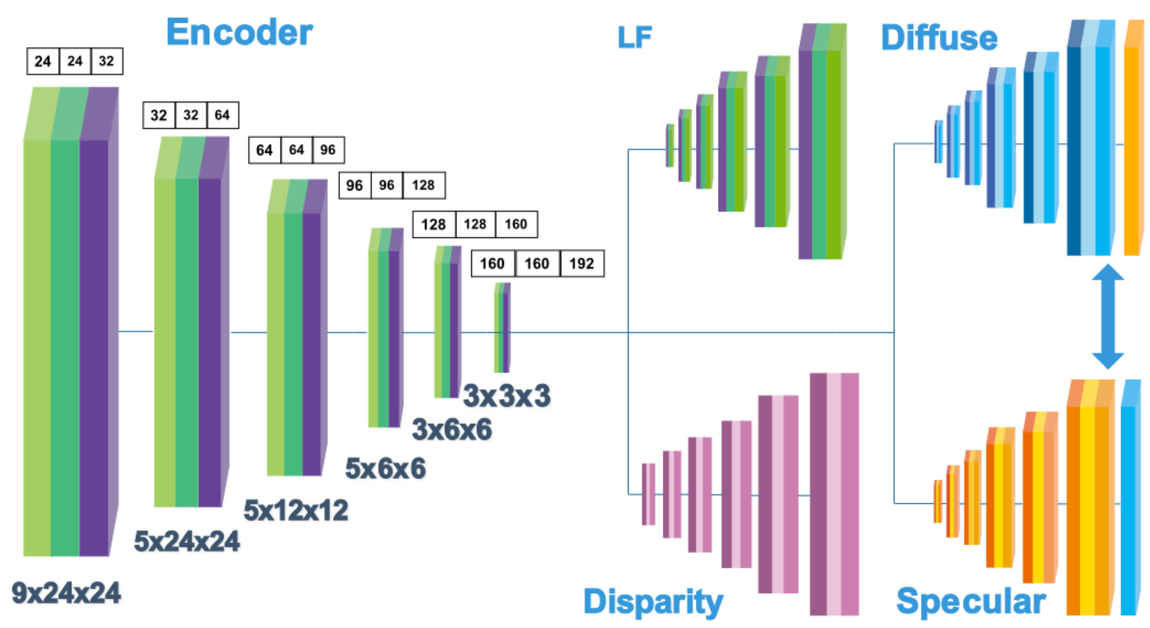



After **batch normalization**, a first path leads through a (possibly strided) **convolution** layer and a **leaky ReLU**.

A second path either keeps the input, or passes it through a strided **convolution** in case it needs to be resampled.

Both paths are added together to produce the final output.

## Network architecture




- Paths:
  - One encoding
  - Four decoding
  - Six groups of three residual blocks each
  - Disparity is a 2D decoder
  - Reconstructed light field, diffuse and specular decoders are 3D
- Block types:
  - depth and resolution the same
  - reduced resolution, while increased feature depth
- Network operates on the horizontal and vertical EPI stacks in parallel
- The feature output is joined on the bottom layer
- Compression rate is $8.3\%$

This work was supported by the ERC Starting Grant
"Light Field Imaging and Analysis" (LIA 336978, FP7-2014).
Presented at the International Conference on Computer Vision and Pattern Recognition (CVPR), Salt Lake City, June 2018.

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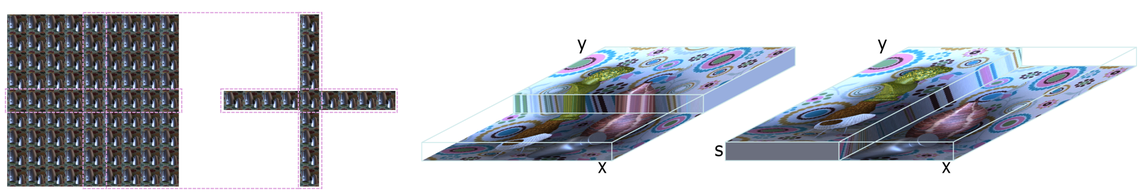
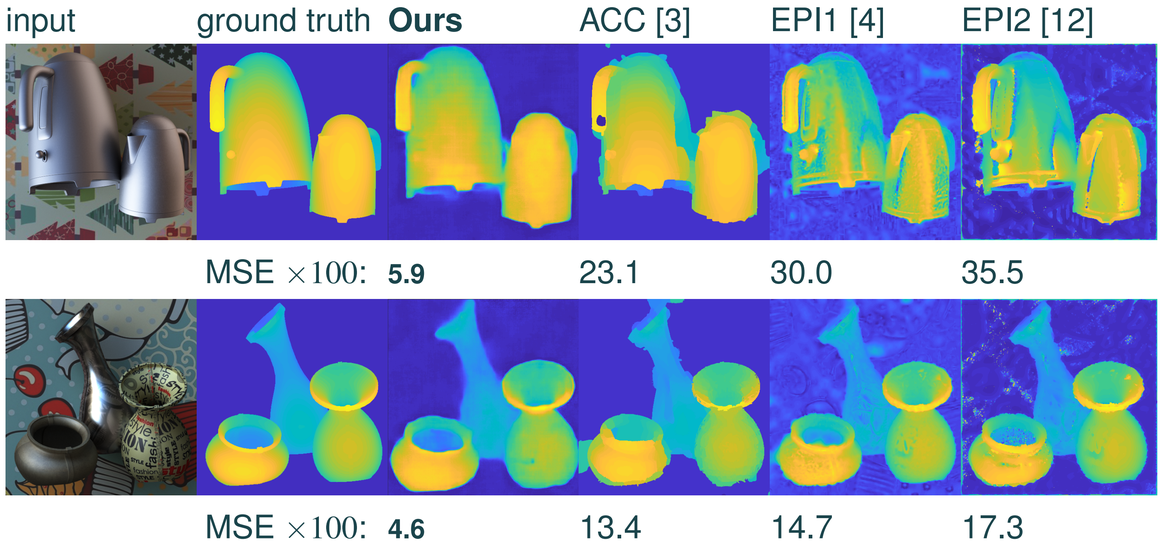
## Network inputs




- crosshair-shaped subset of 17 views
- patch size $9 \times 48 \times 48$
- $\approx 160,000$ patches

## Comparisons on the synthetic light fields

### disparity



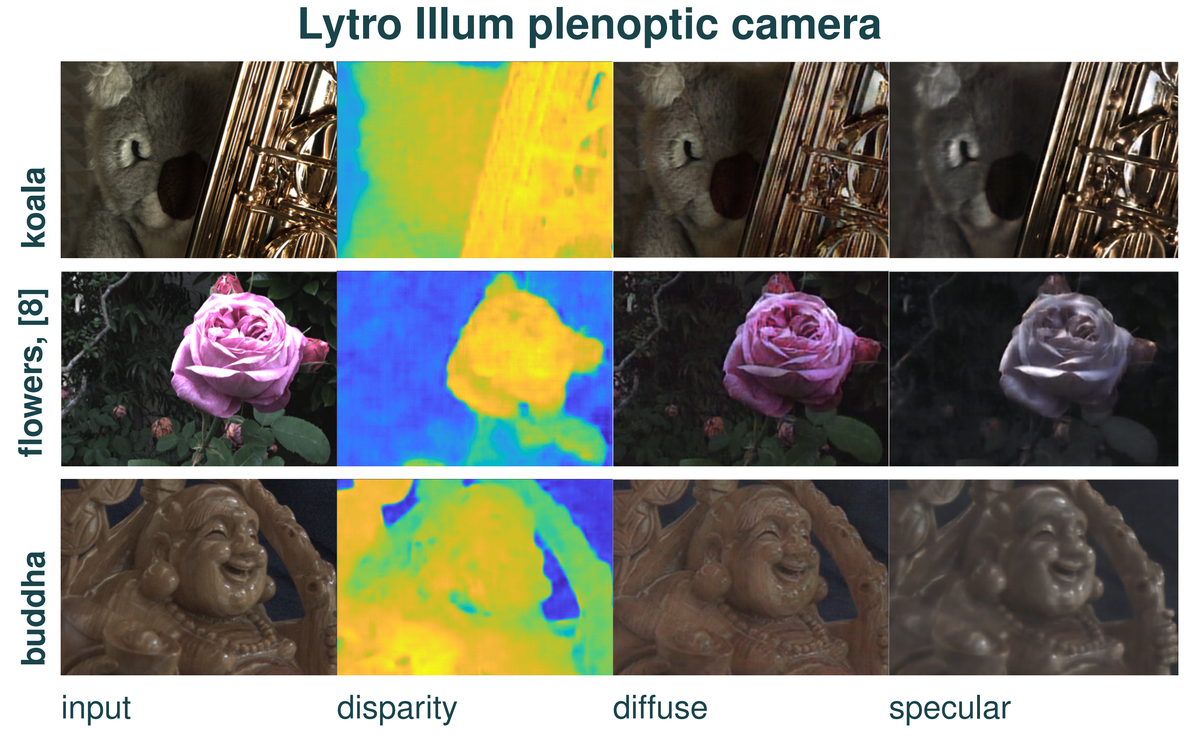

### reflection separation


### numerical results

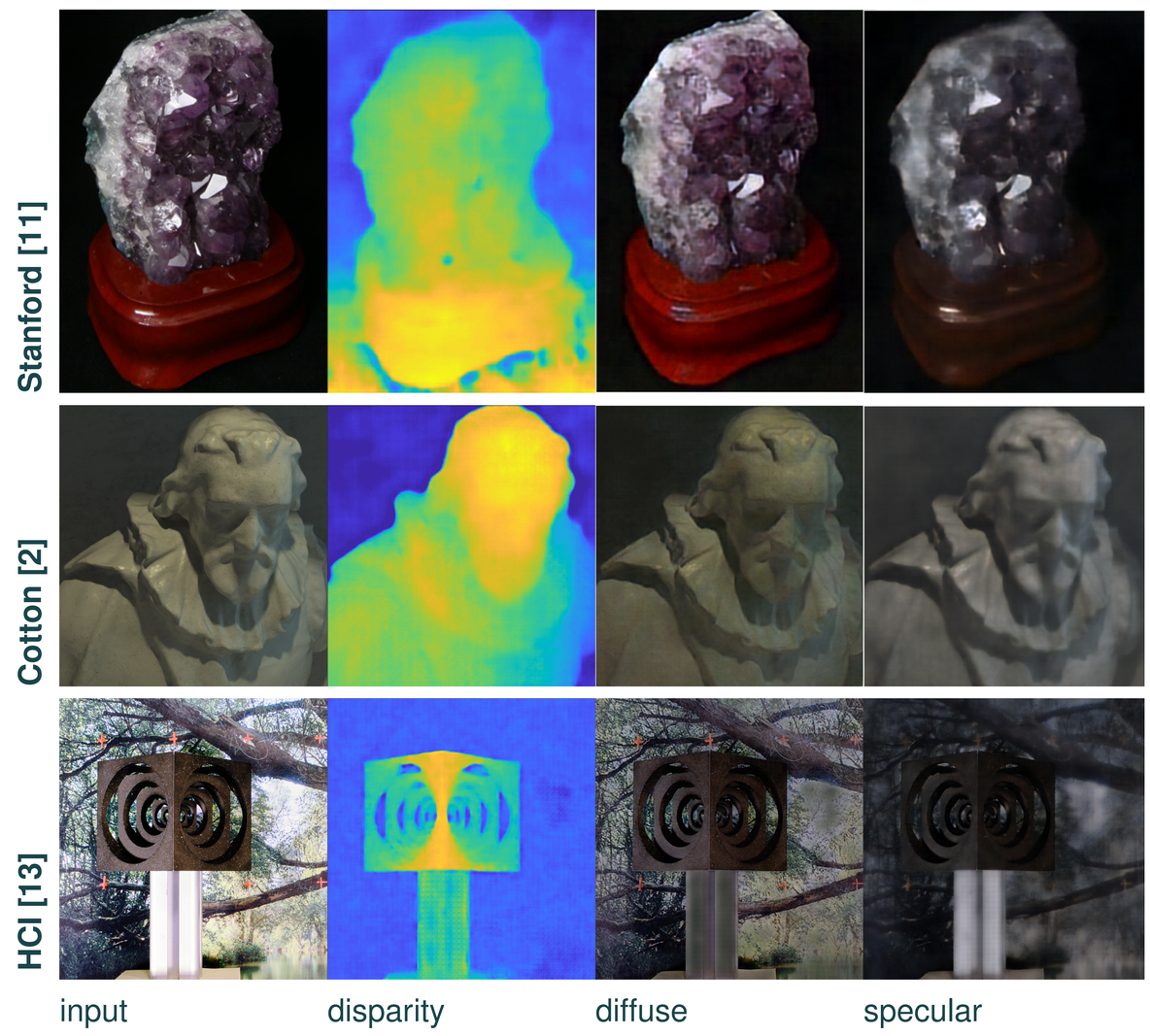
| | LMSE ×100 | | GMSE ×100 | | SSIM ×100 | |
|---|---|---|---|---|---|---|
| | diff. | spec. | diff. | spec. | diff. | spec. |
| **Ours** | 0.15 | **0.11** | 0.28 | **0.23** | **80.08** | **81.37** |
| Alperovich [1] | **0.12** | 0.45 | **0.22** | 1.04 | 74.98 | 48.46 |
| Sulc et al. [9] | **0.12** | 0.47 | 0.24 | 1.01 | 75.43 | 47.25 |
| Shi et al. [7] | 0.34 | 0.15 | 0.5 | 0.39 | 63.02 | 73.71 |

## Results for the real-world and synthetic light fields

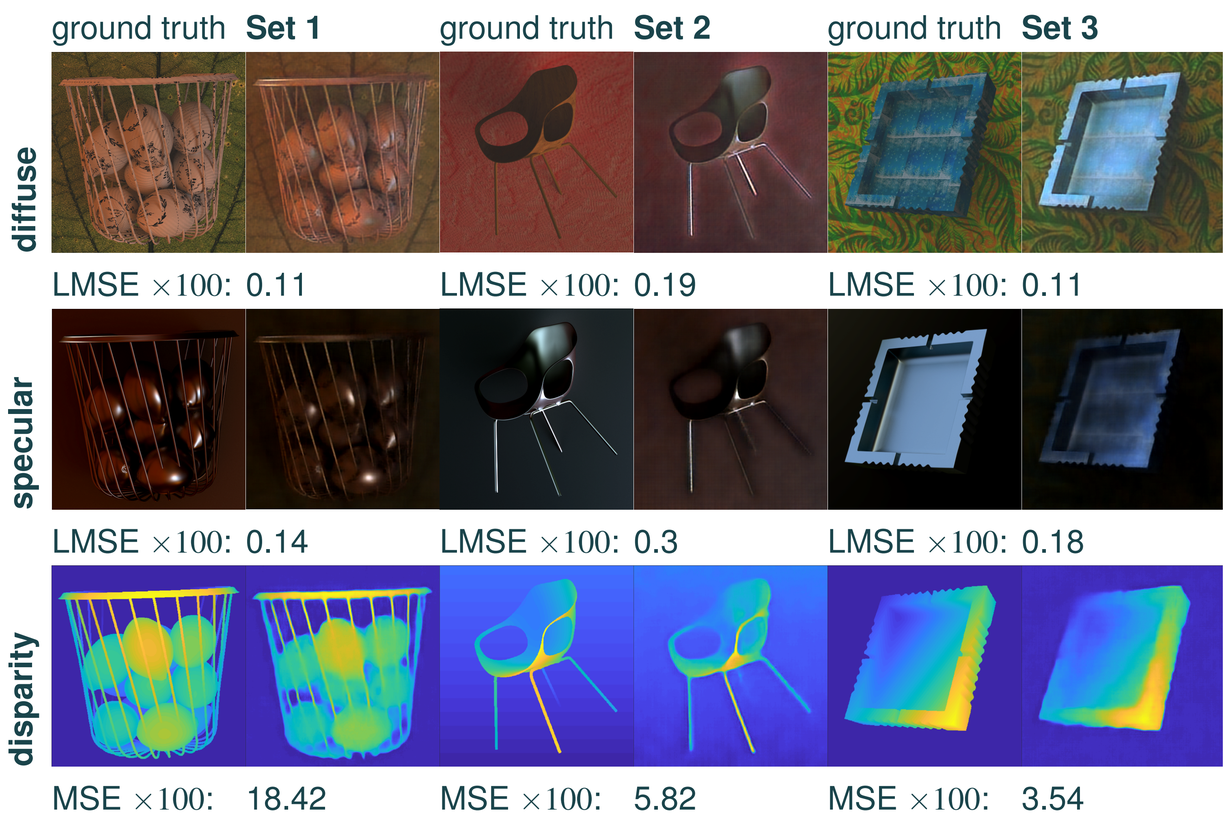
### Lytro Illum plenoptic camera




### various sources




## Visual and quantitative evaluations

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