A second-order theory of texture for depth from focus

a.k.a. depth from focus for (seemingly) textureless surfaces

Sreekar Ranganathan and Ioannis Gkioulekas

Carnegie Mellon University

CVPR 1997

Are Textureless Scenes Recoverable?

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Abstract

It is widely accepted that textureless surfaces cannot be recovered using passive sensing techniques. The problem is approached by viewing image formation as a fully three-dimensional mapping. It is shown that the lens encodes structural information of the scene within a compact three-dimensional space behind it. After analyzing the information content of this space and by using its properties we derive necessary and sufficient conditions for the recovery of textureless scenes. Based on these conditions, a simple procedure for recovering textureless scenes is described. We experimentally demonstrate the recovery of three textureless surfaces, namely, a line, a plane, and a paraboloid. Since textureless surfaces represent the worst case recovery scenario, all the results and the recovery procedure are

in a compact three-dimensional space behind the imaging lens. We refer to this space as the *monocular visual space* (MVS). An image is but a two-dimensional slice (frontal, non-frontal, or even curved) through this space. Rather than asking how much more than what is already known can be recovered from an image, we explore what information about the three-dimensional scene is captured within the monocular space. Similar studies have been conducted earlier in the context of optical microscopy [Streibl 85]. However, the object illumination, the imaging optics, and the sensing methods differ significantly from those of a conventional imaging system used in computational vision.

If we image the world using a pinhole camera, the MVS is completely determined by any one slice (image) through it, since all images in the MVS are simply projective transformations of each other. It turns out that the lens used in

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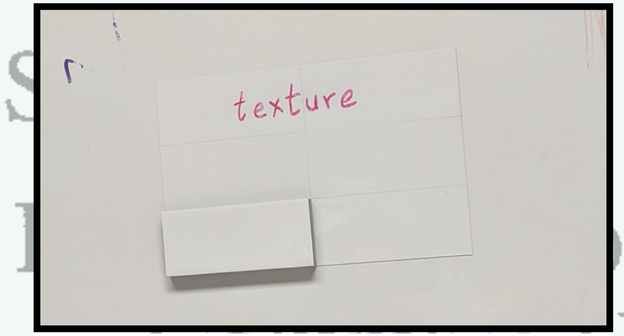
Are Textureless Scenes Recoverable?



textureless scene

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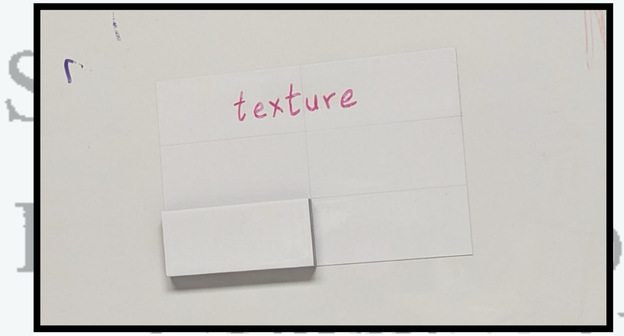

textureless scene

Very little information on depth of a scene

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Are Textureless Scenes Recoverable?

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Yes, with just a color filter. Sci

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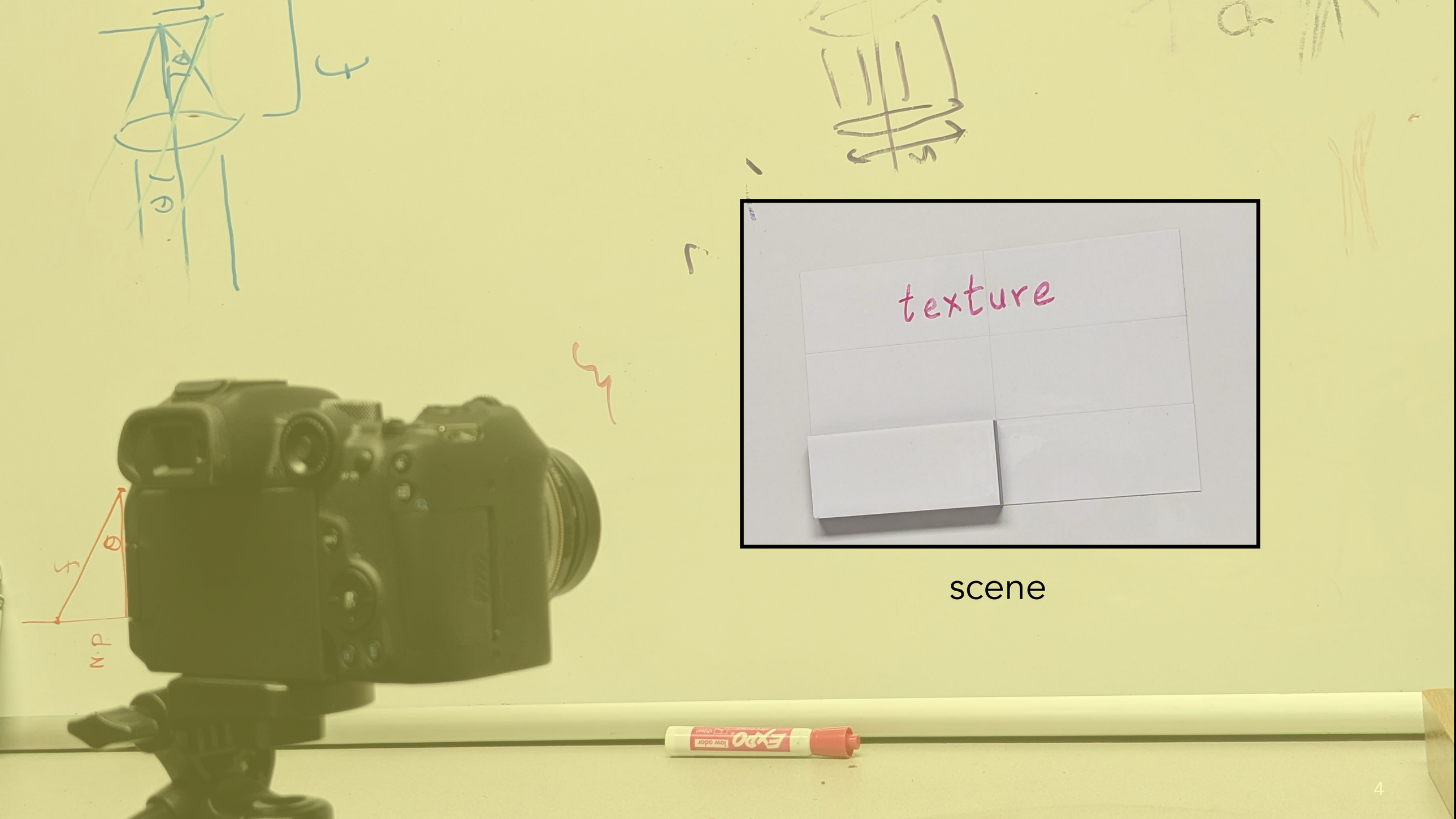
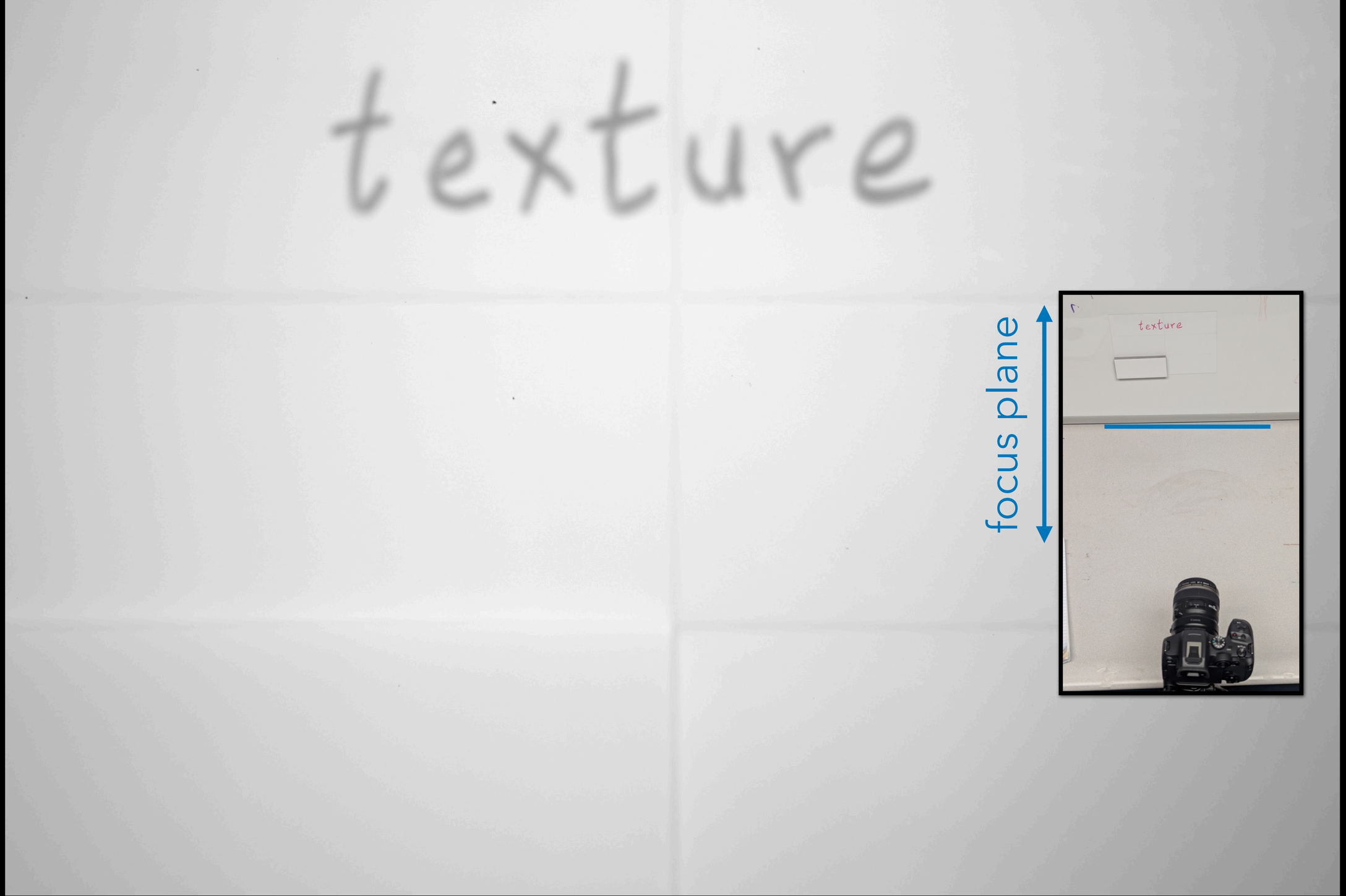
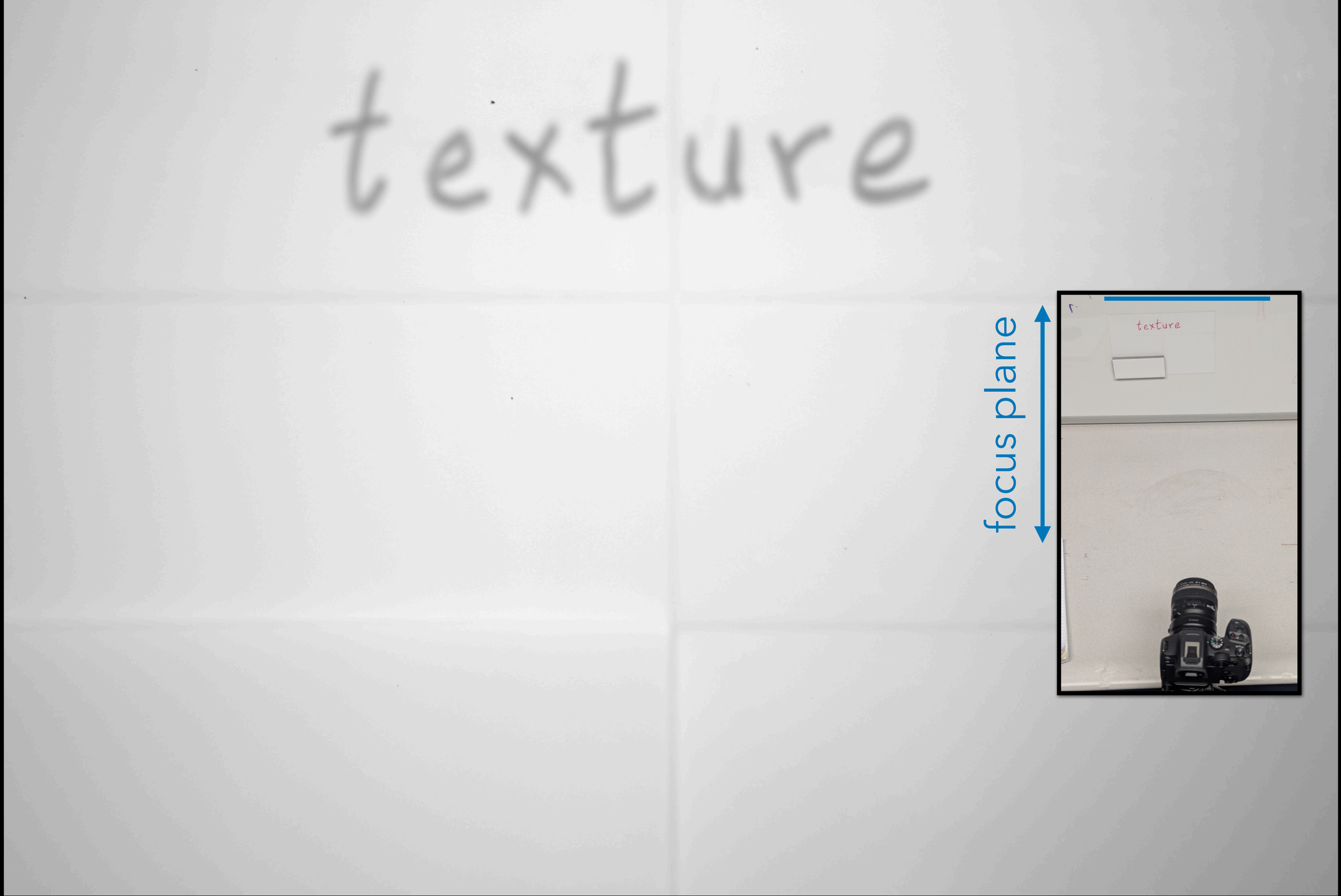
texture
N.P


texture
scene

texture
AF-ON
INFO
SET

camera rig


texture
focus plane
texture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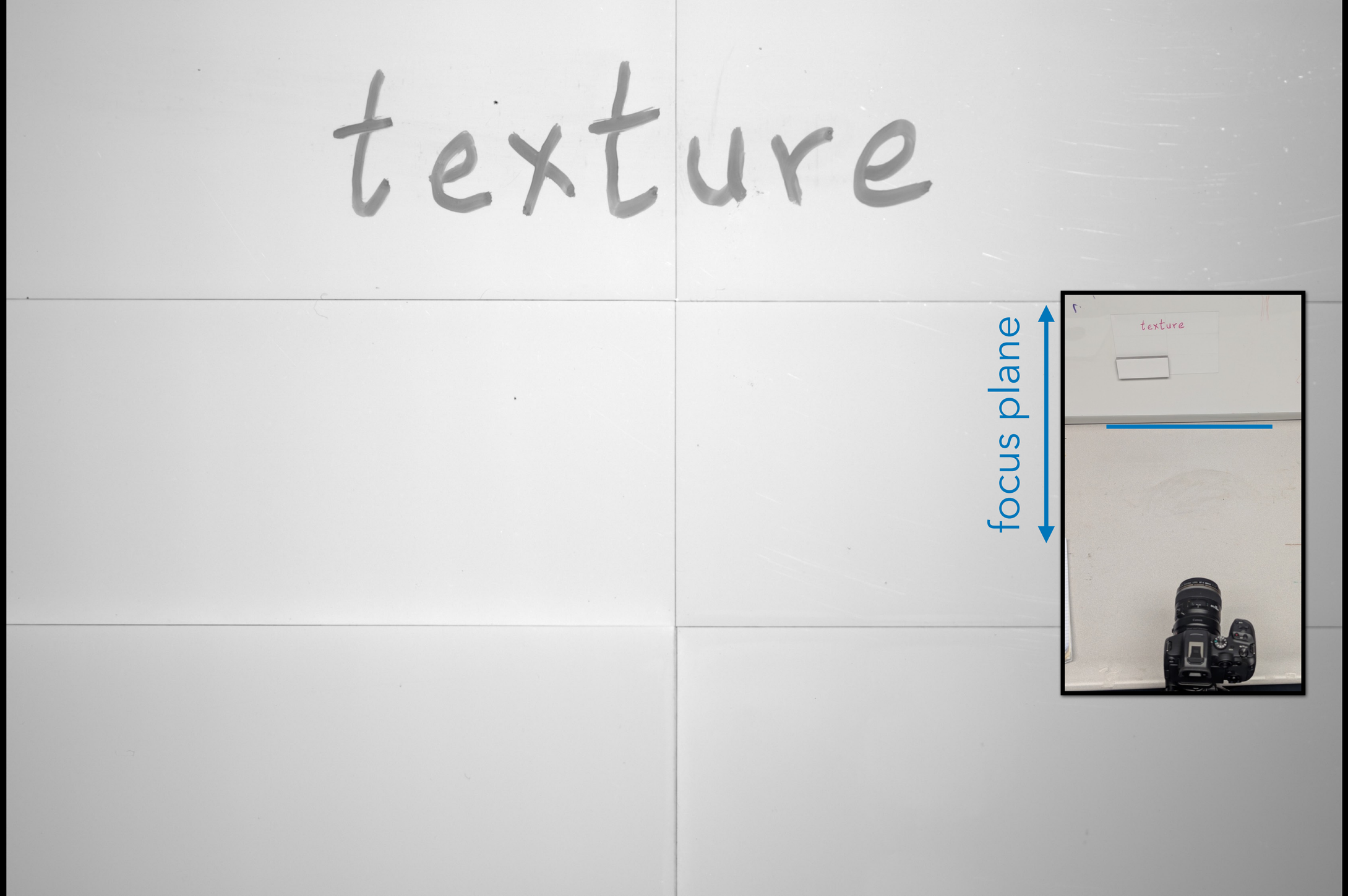
focus plane
texture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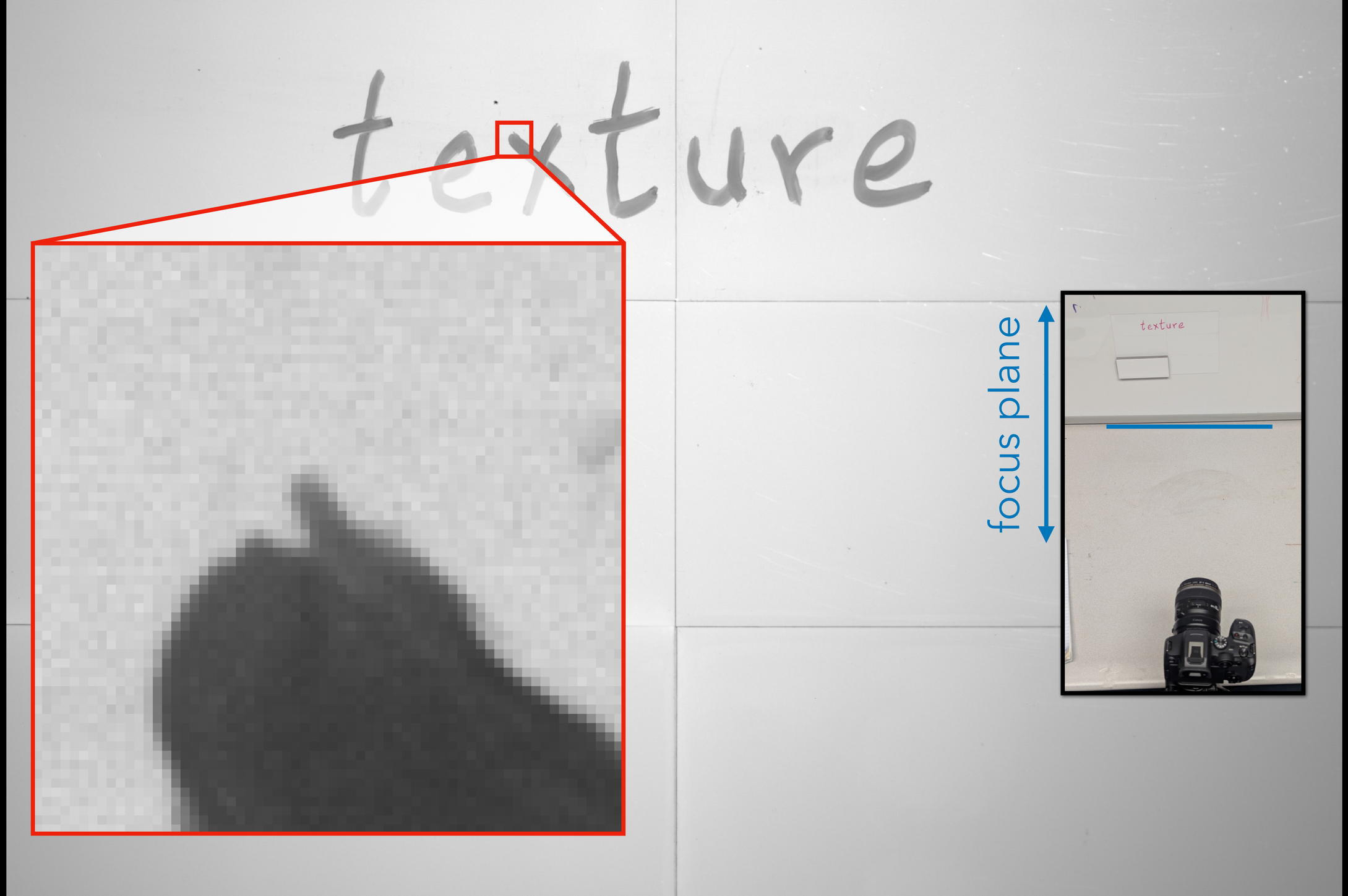
focus plane
texture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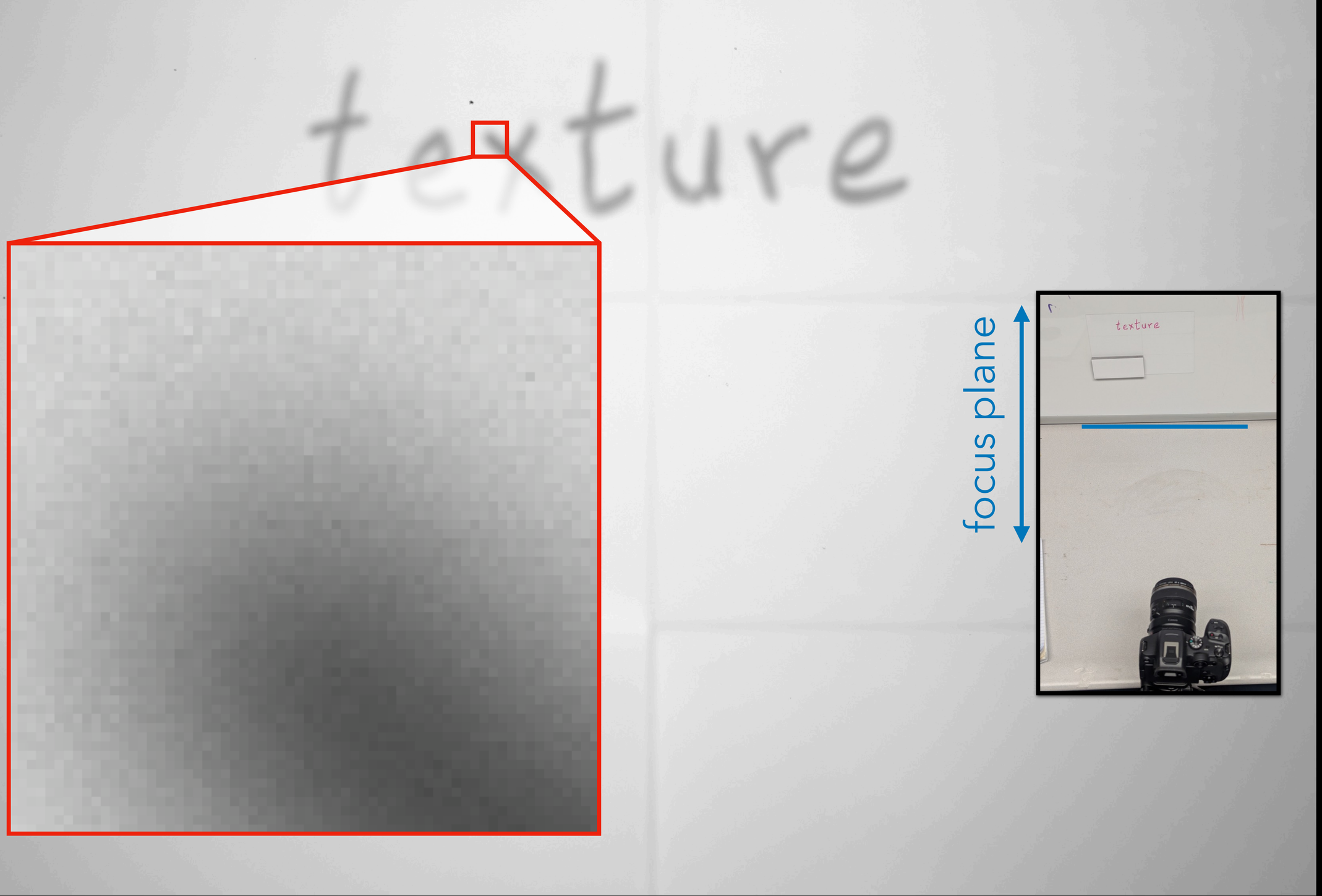
focus plane
texture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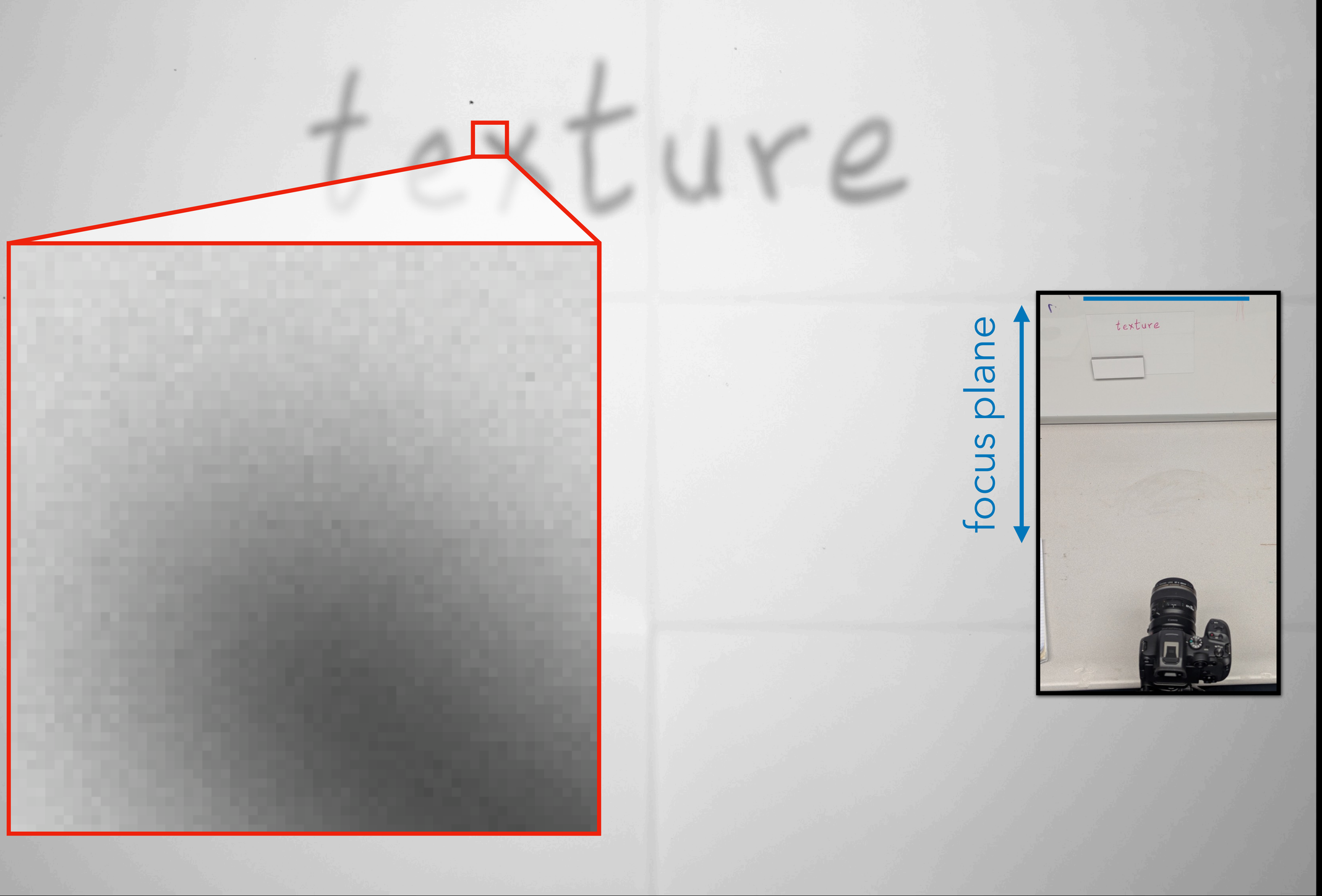
focus plane
texture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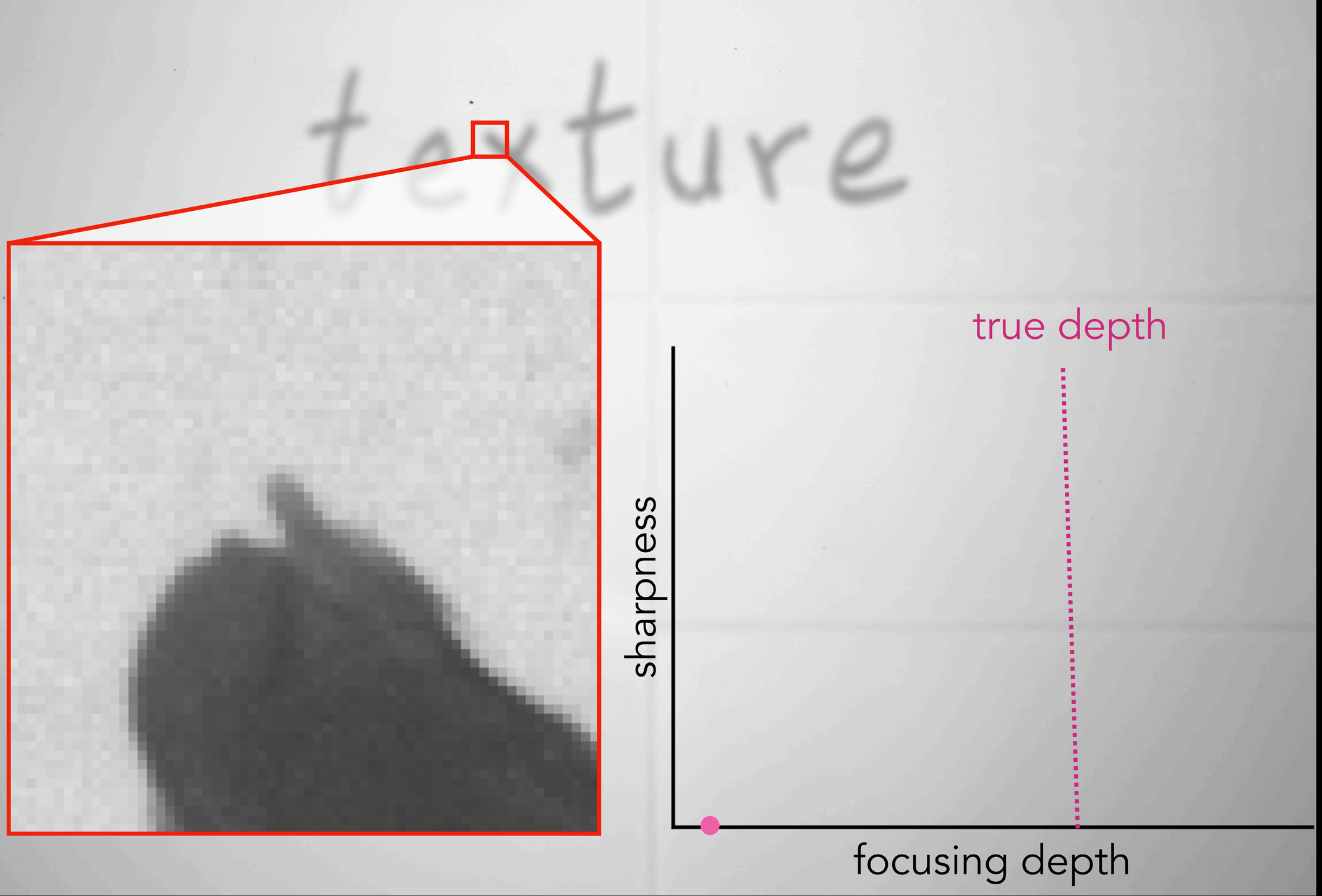
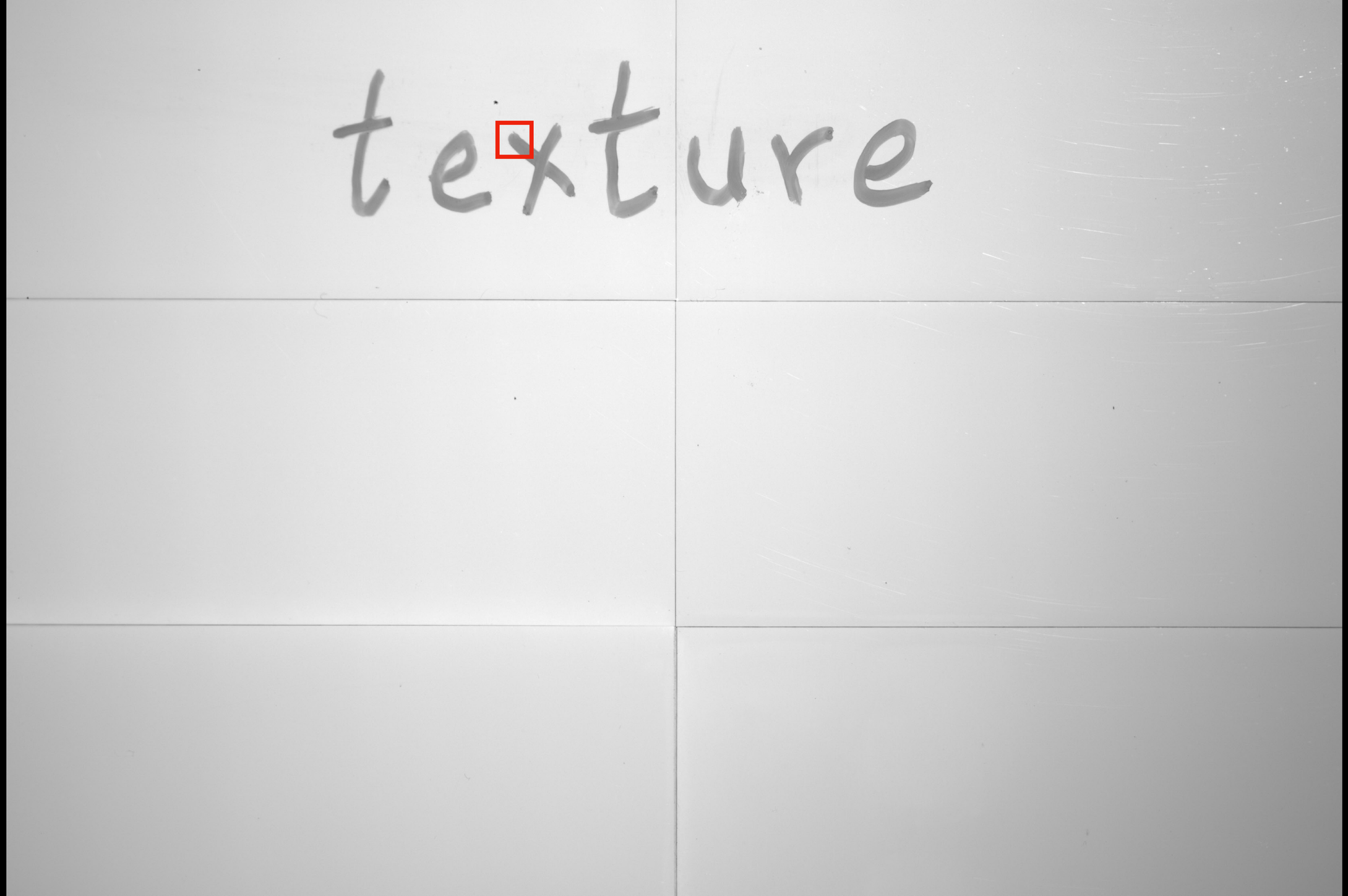
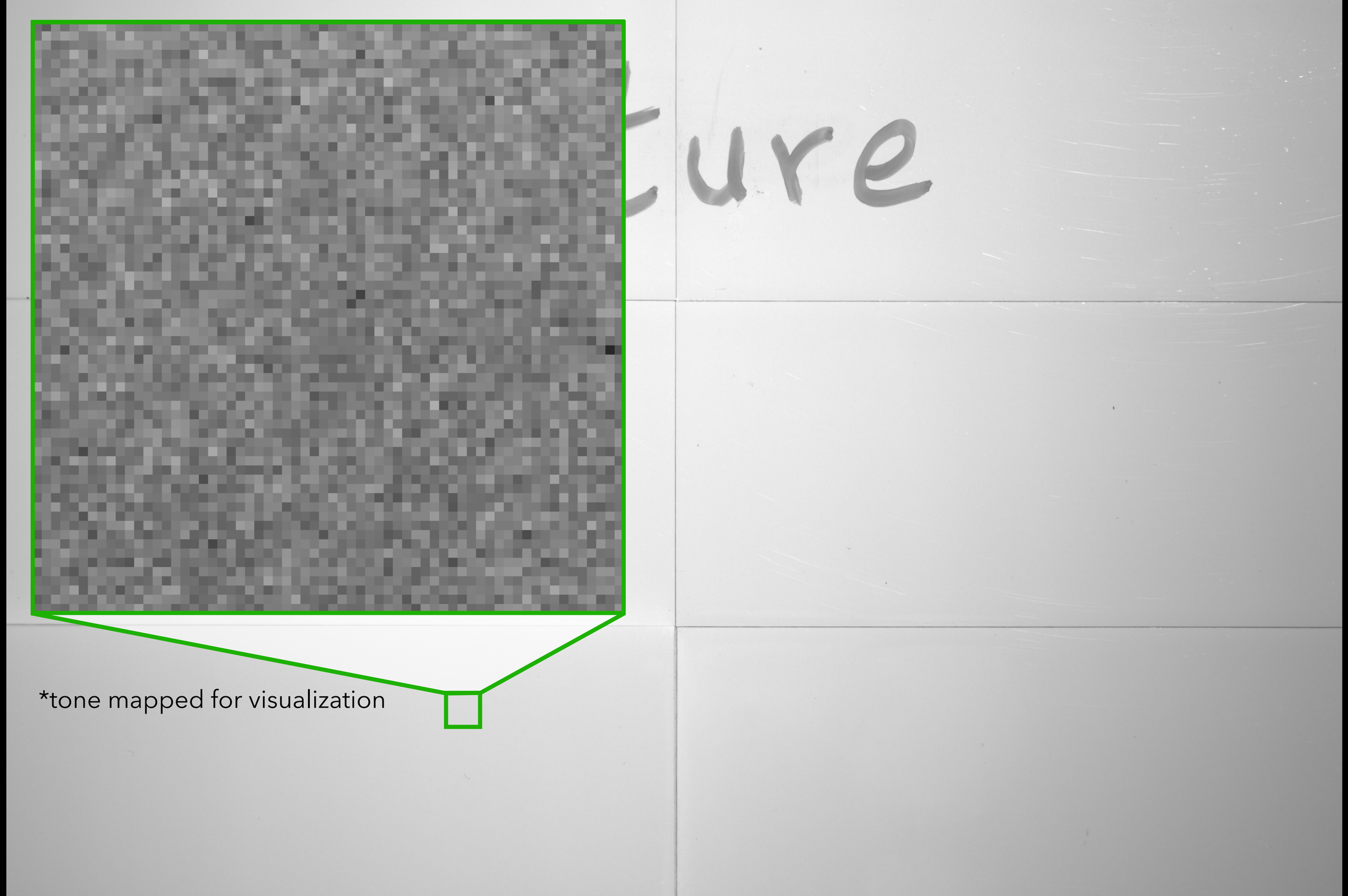
focus plane
texture


texture
true depth
sharpness
focusing depth

texture
true depth
sharpness
focusing depth


texture

texture



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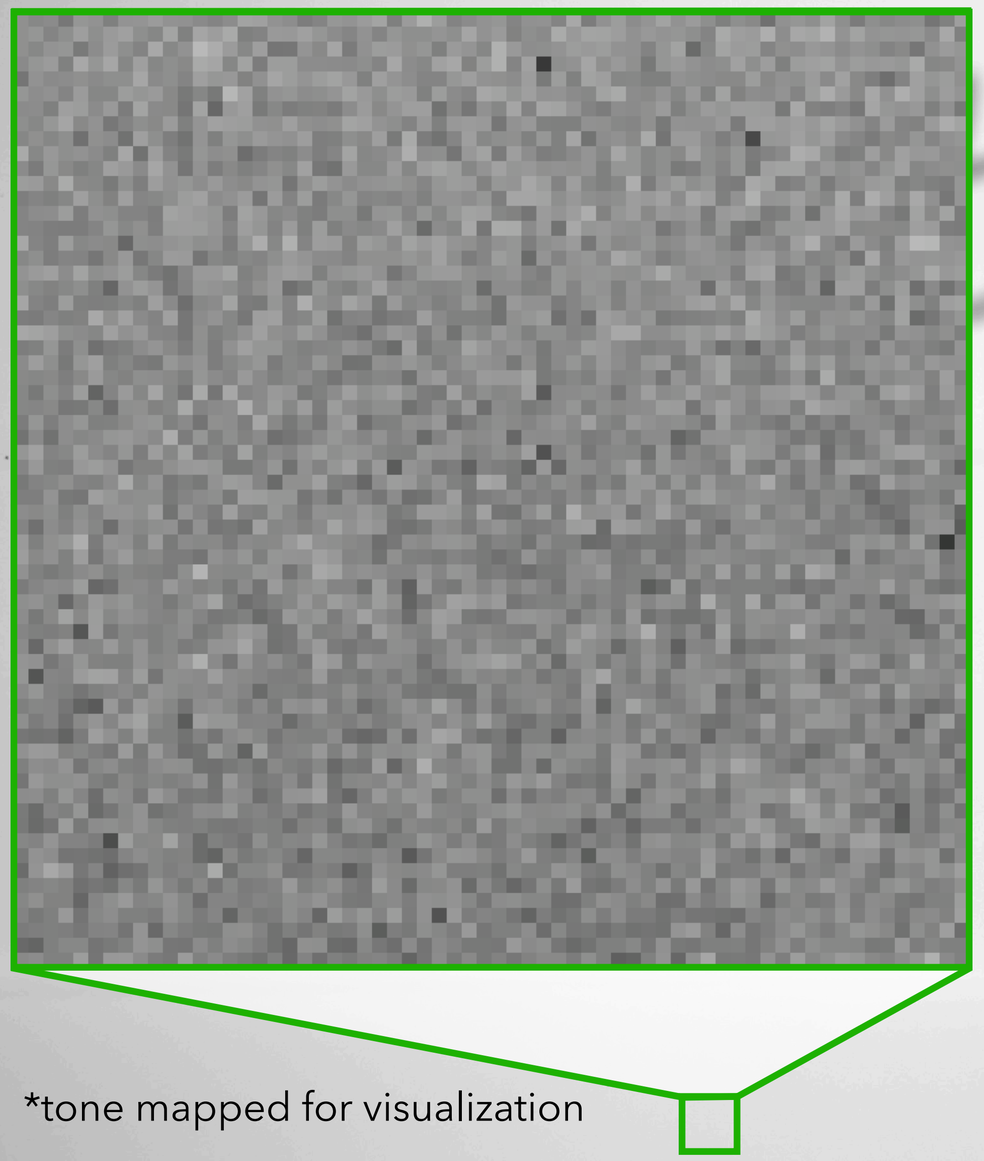

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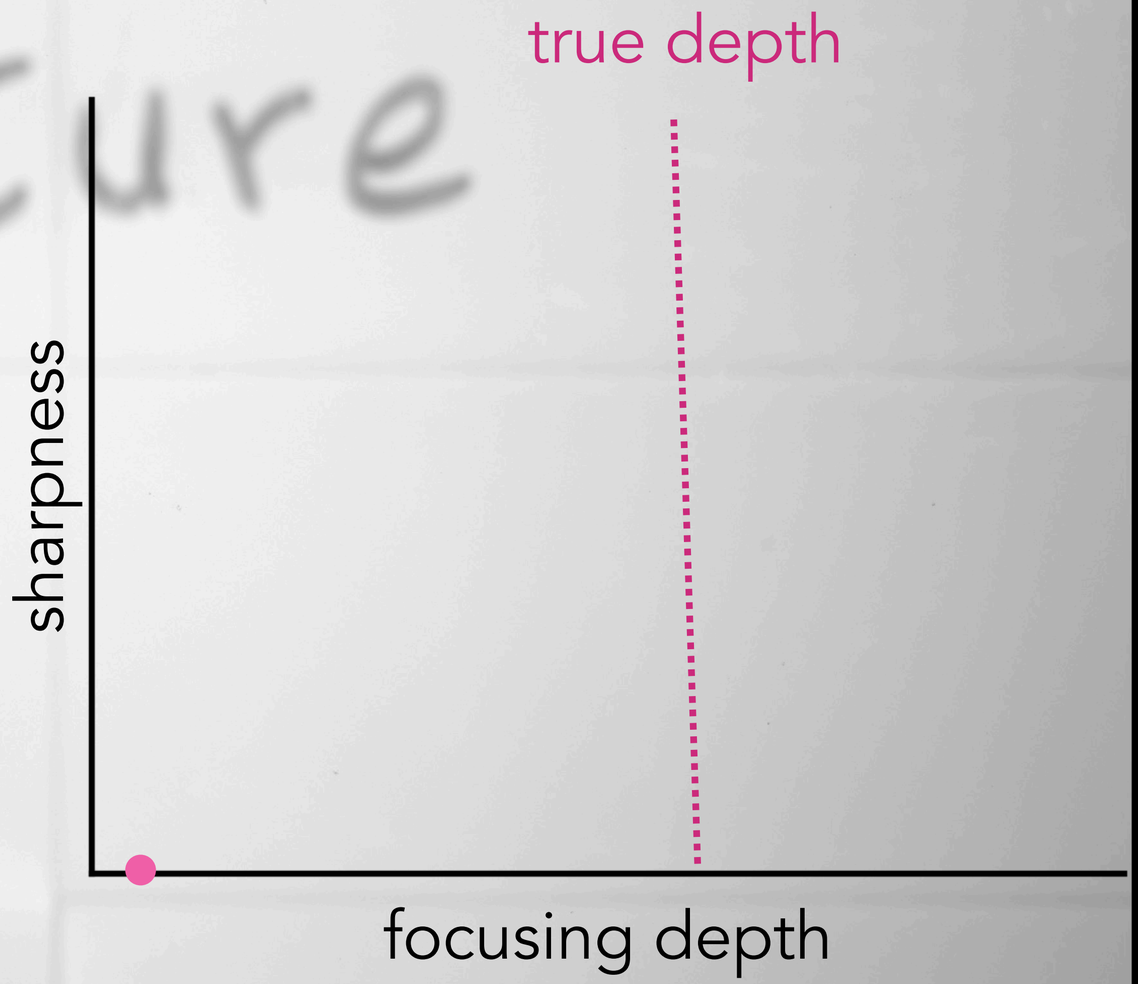

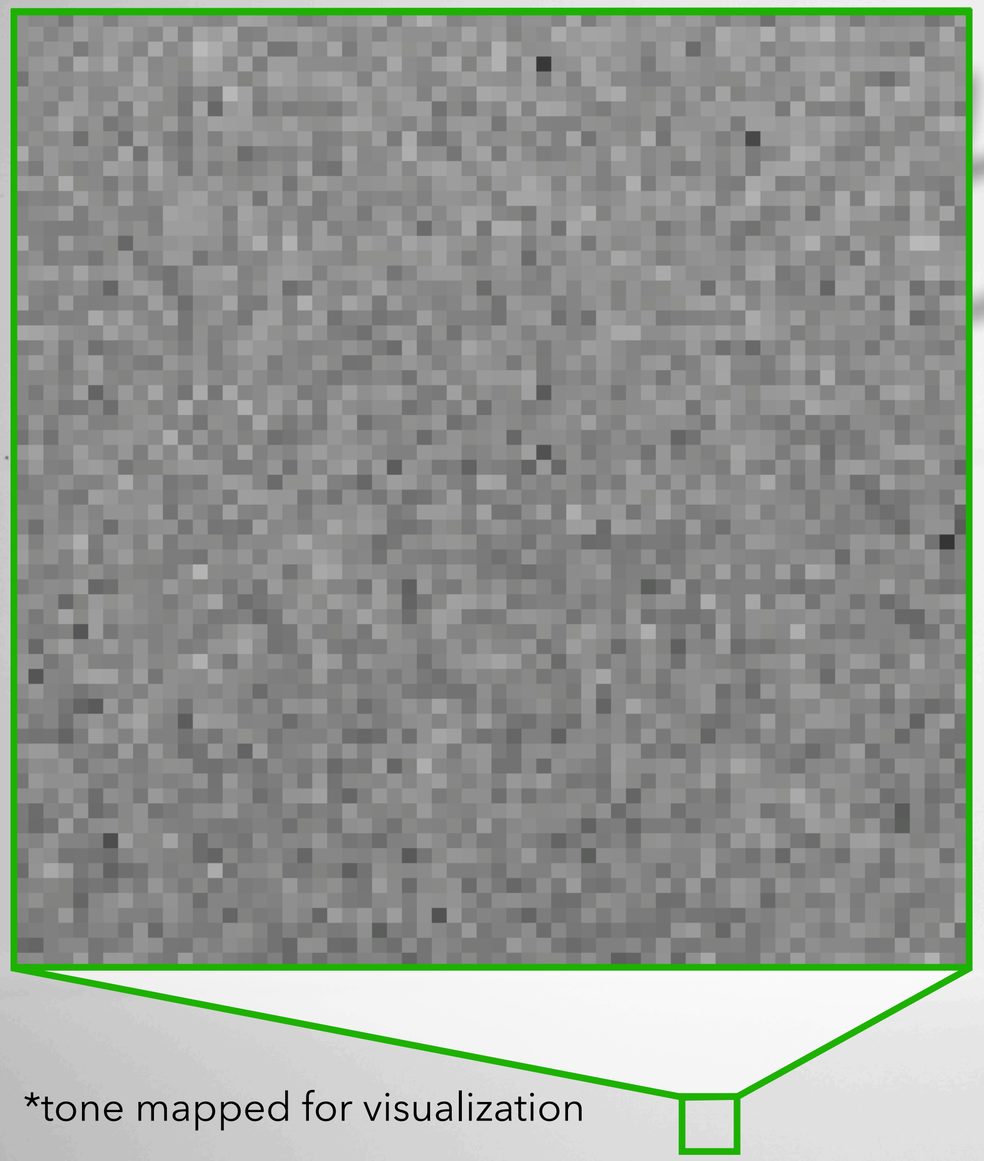

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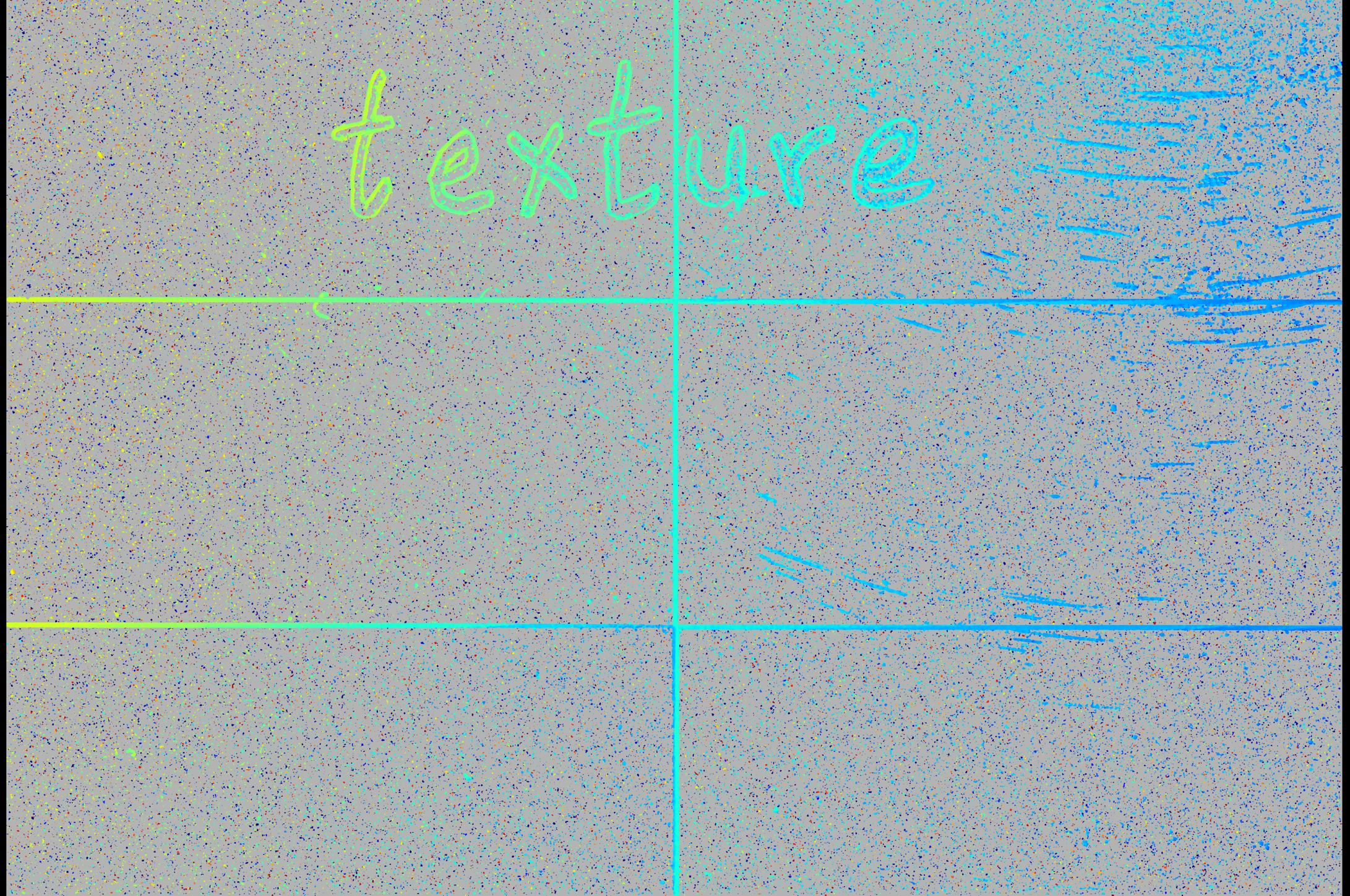
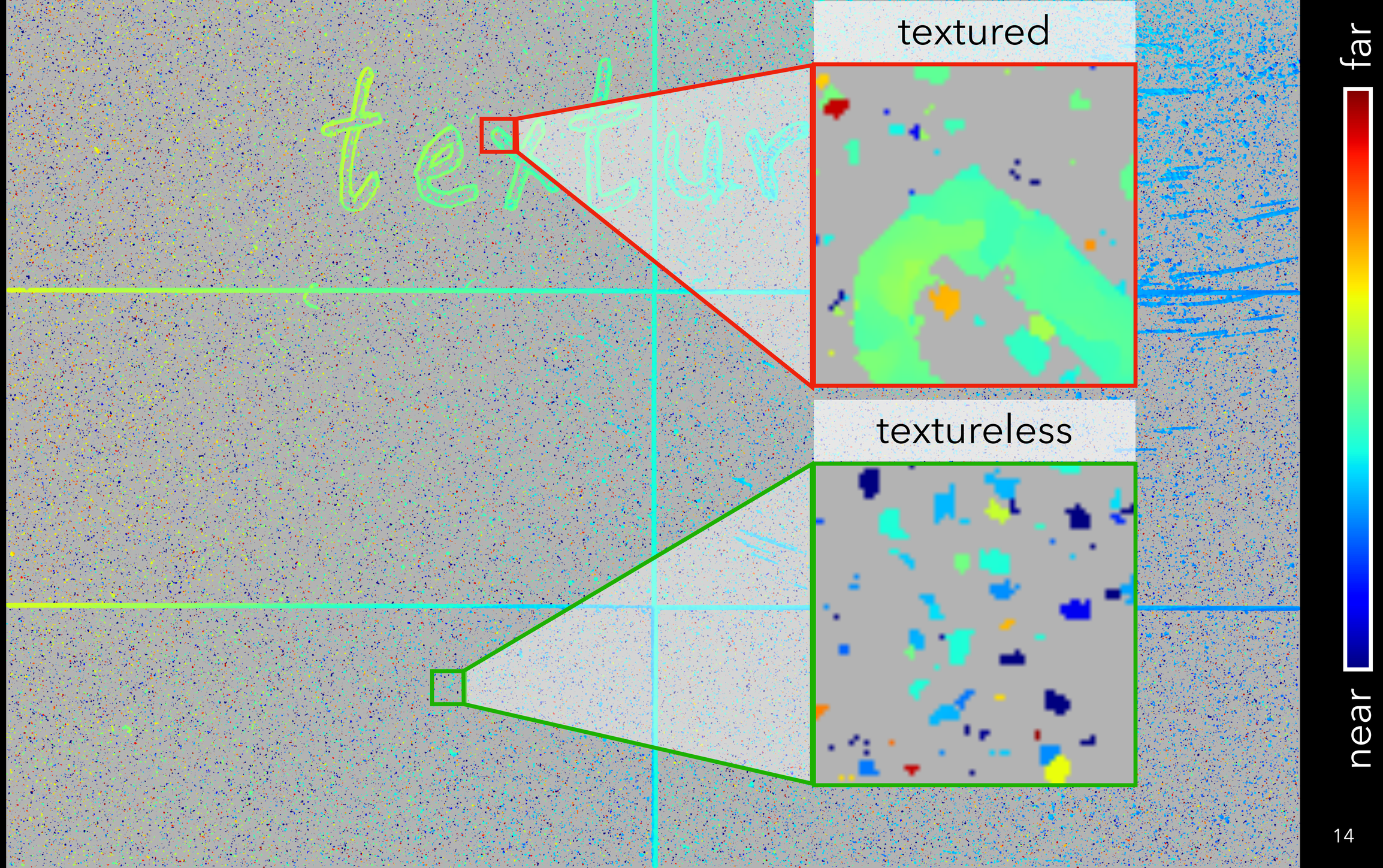
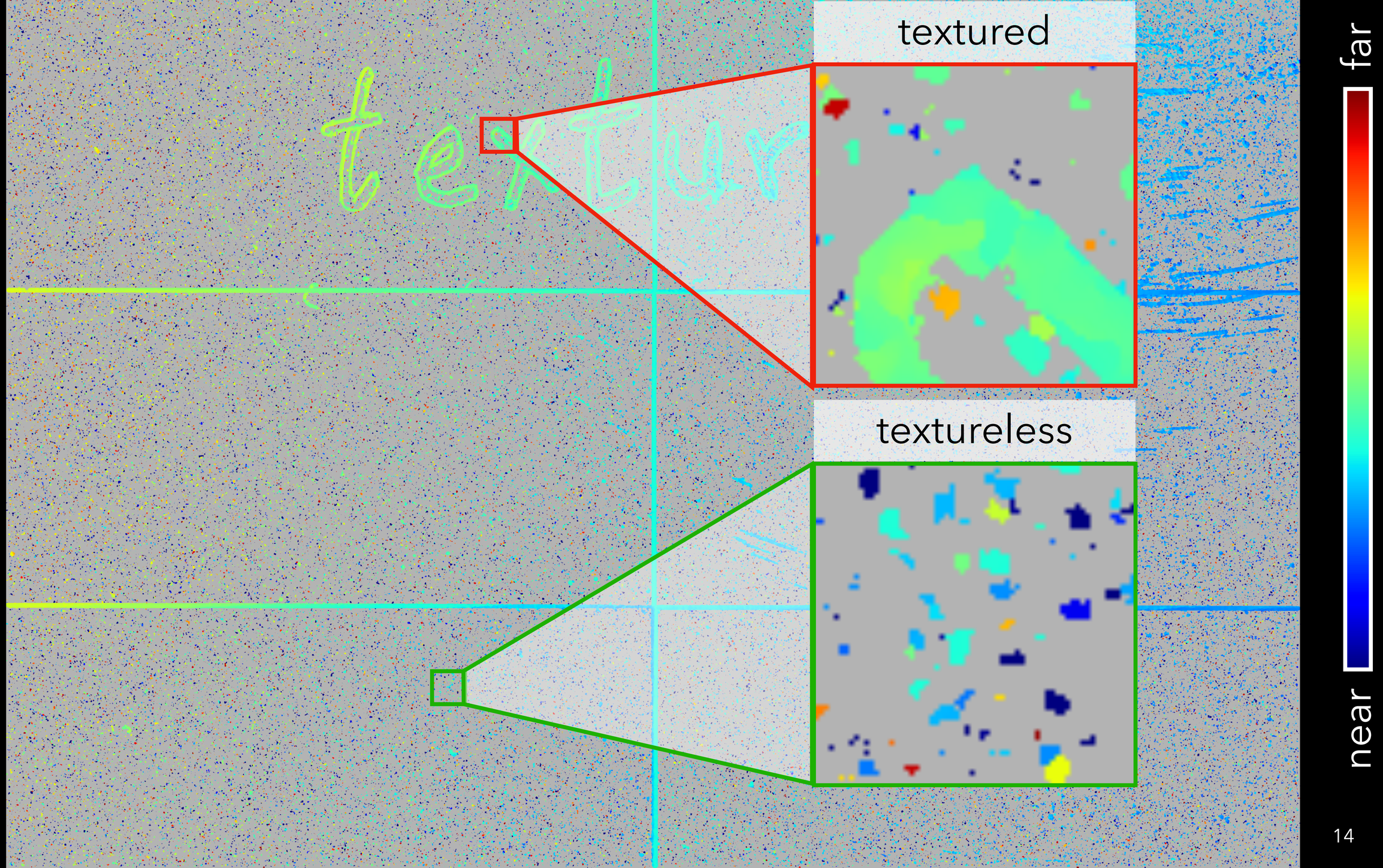
texture



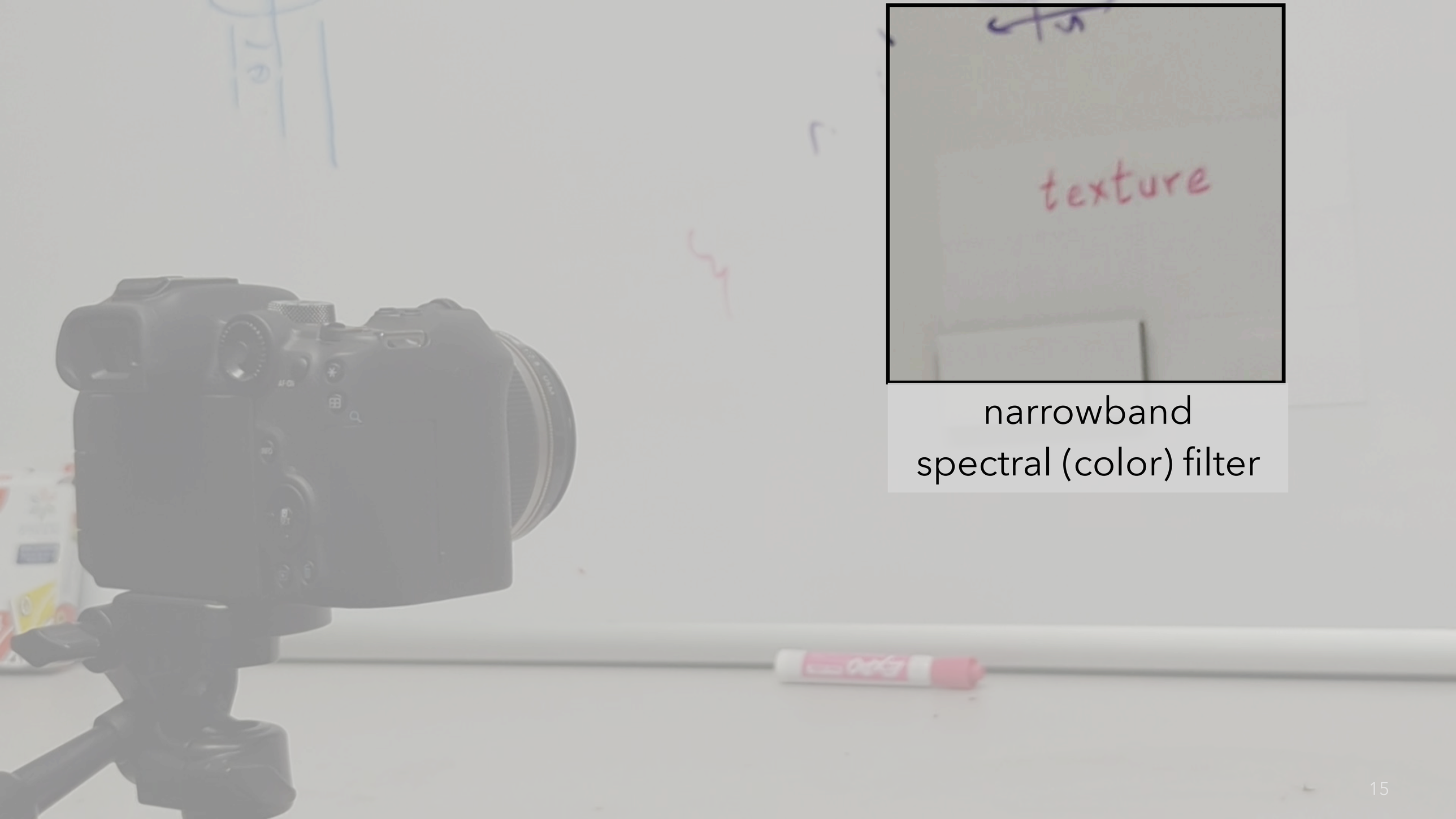
far

near

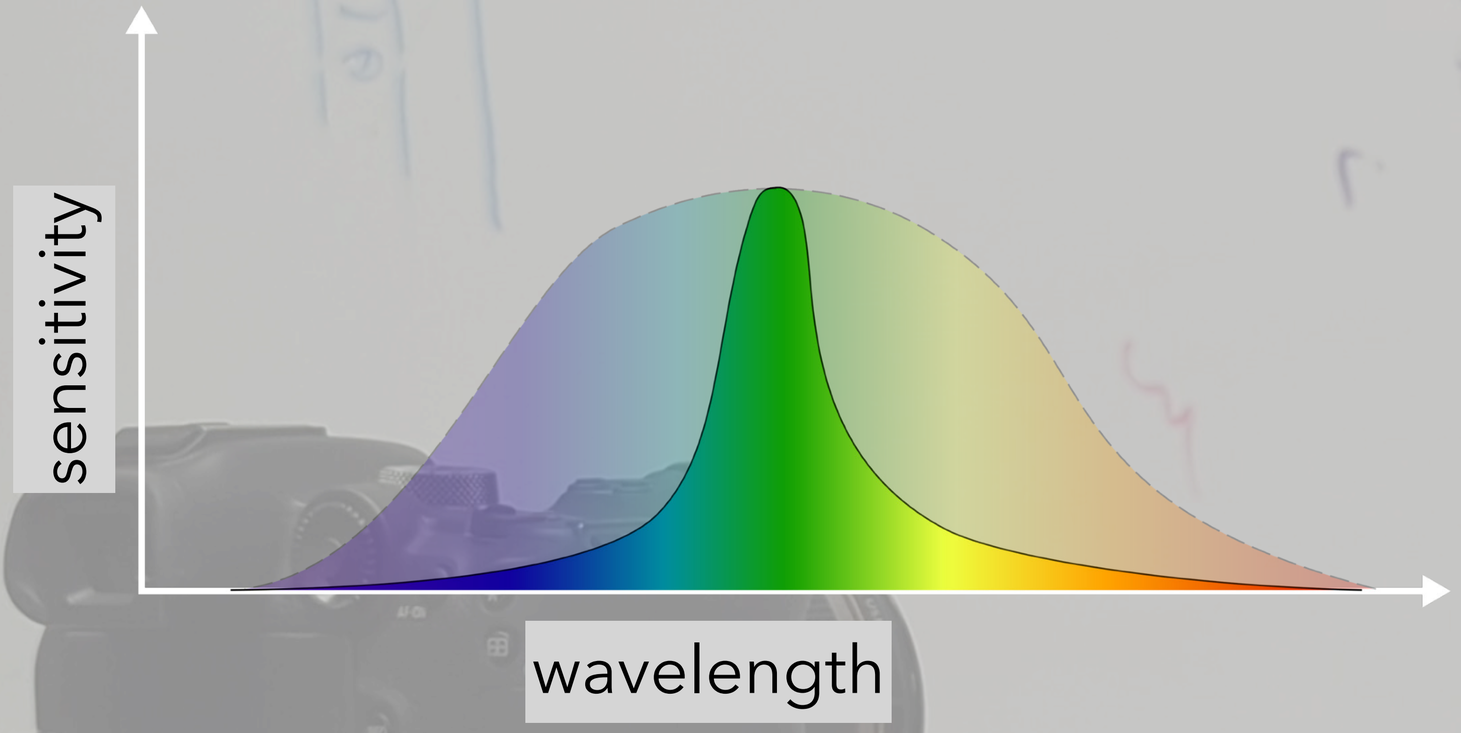

textured
textureless
far
near

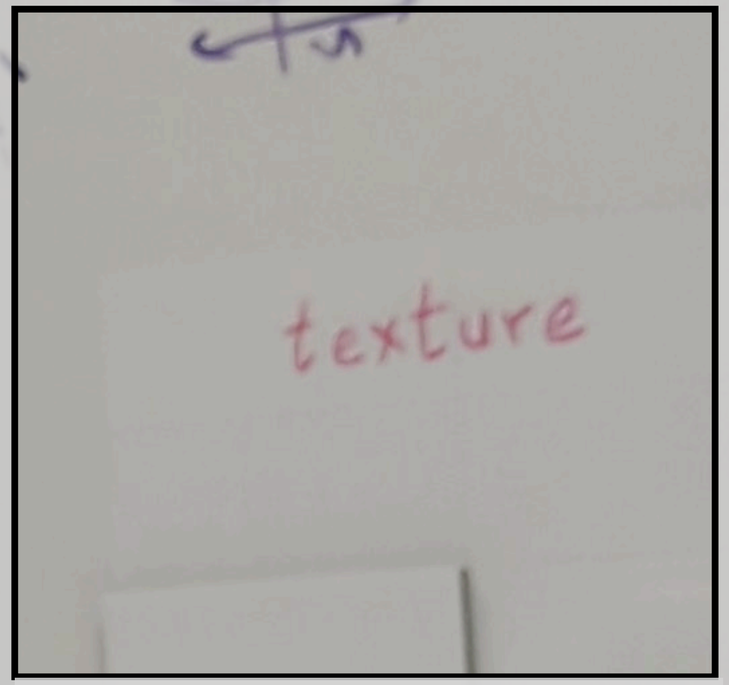

textured
textureless
far
near

texture



narrowband
spectral (color) filter





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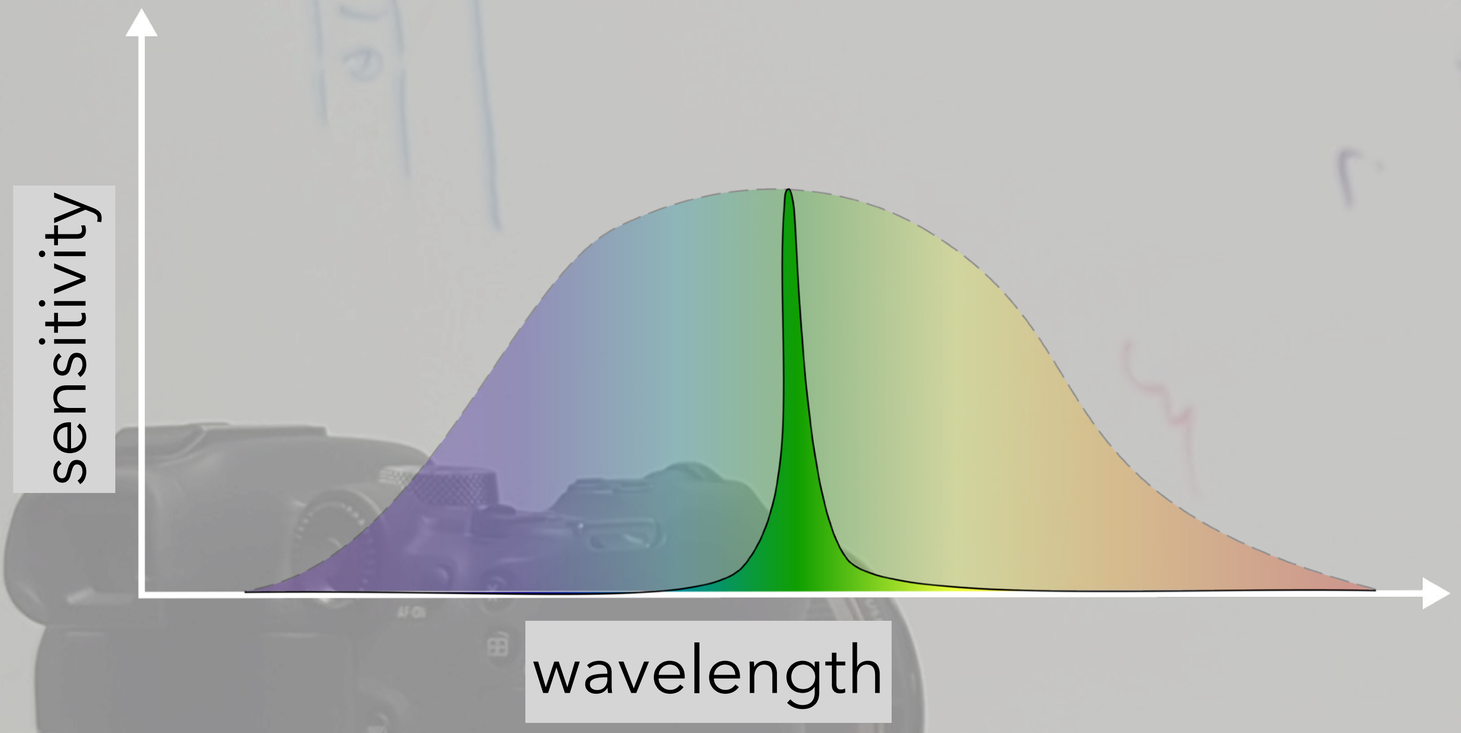
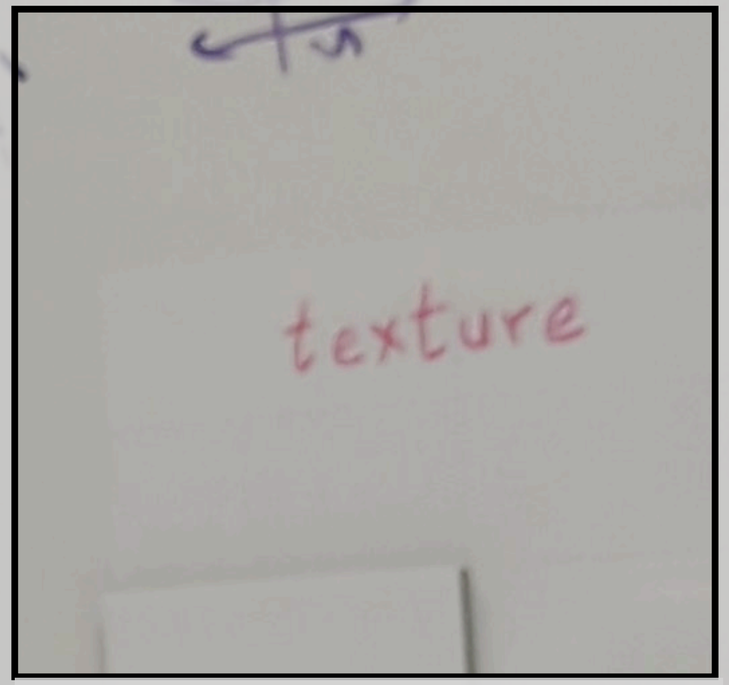
spectral (color) filter



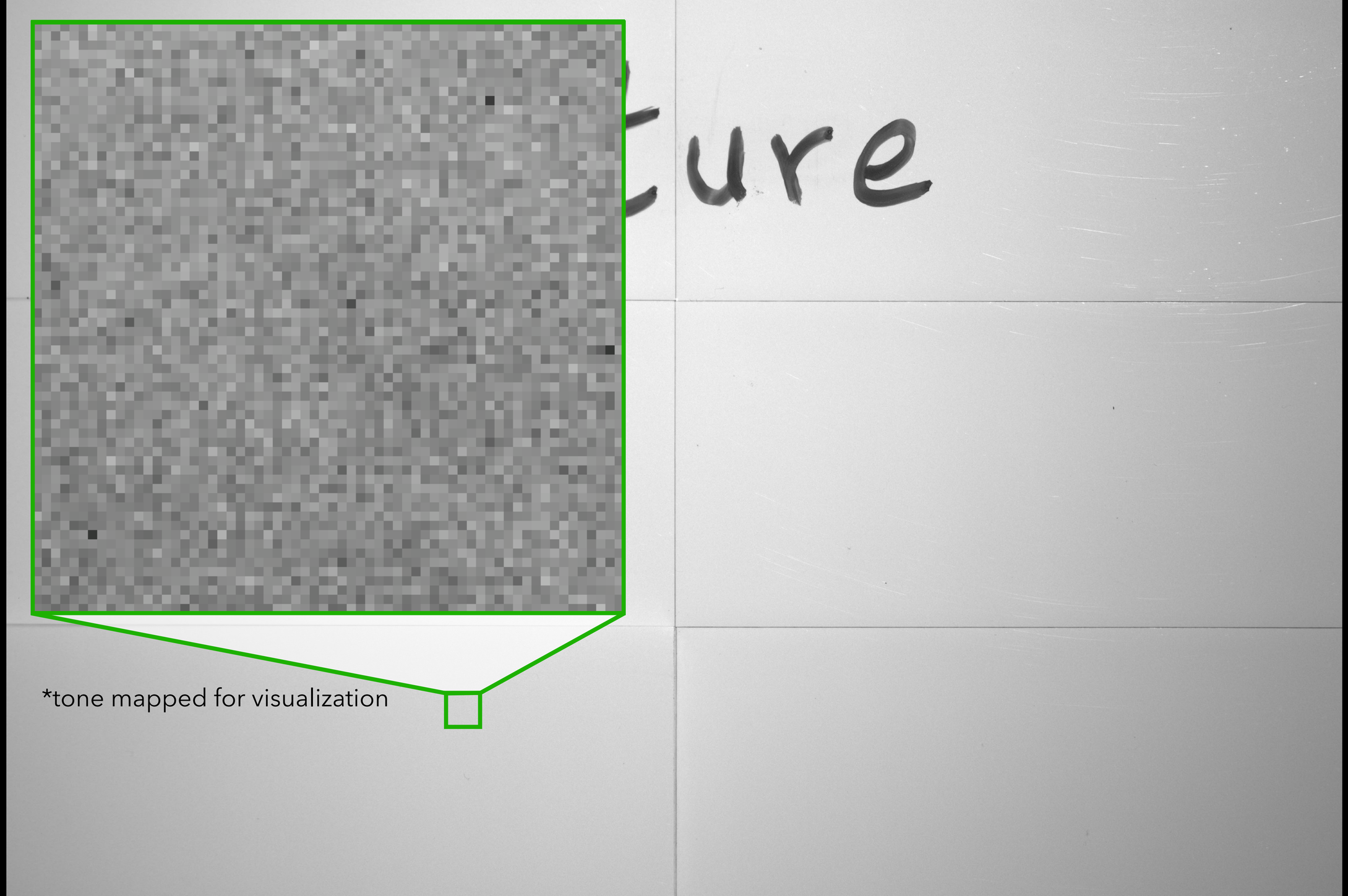


narrowband
spectral (color) filter

texture

texture

texture



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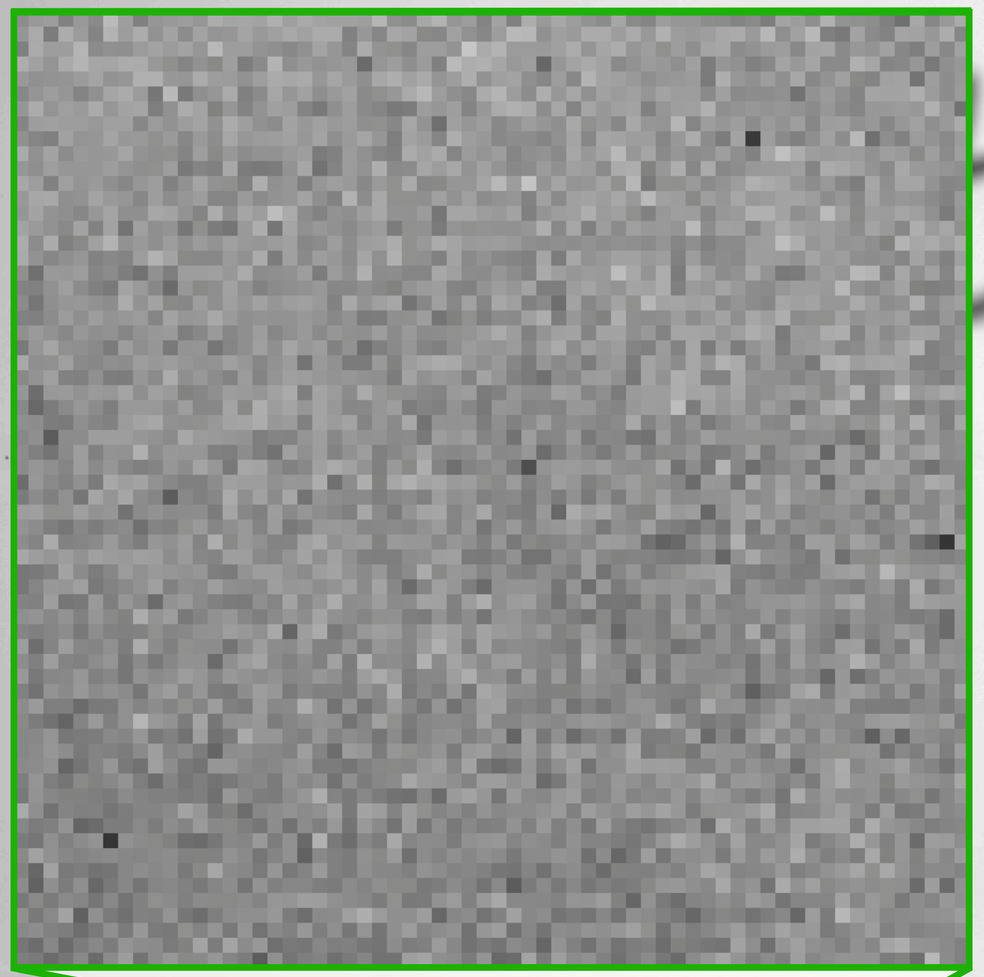

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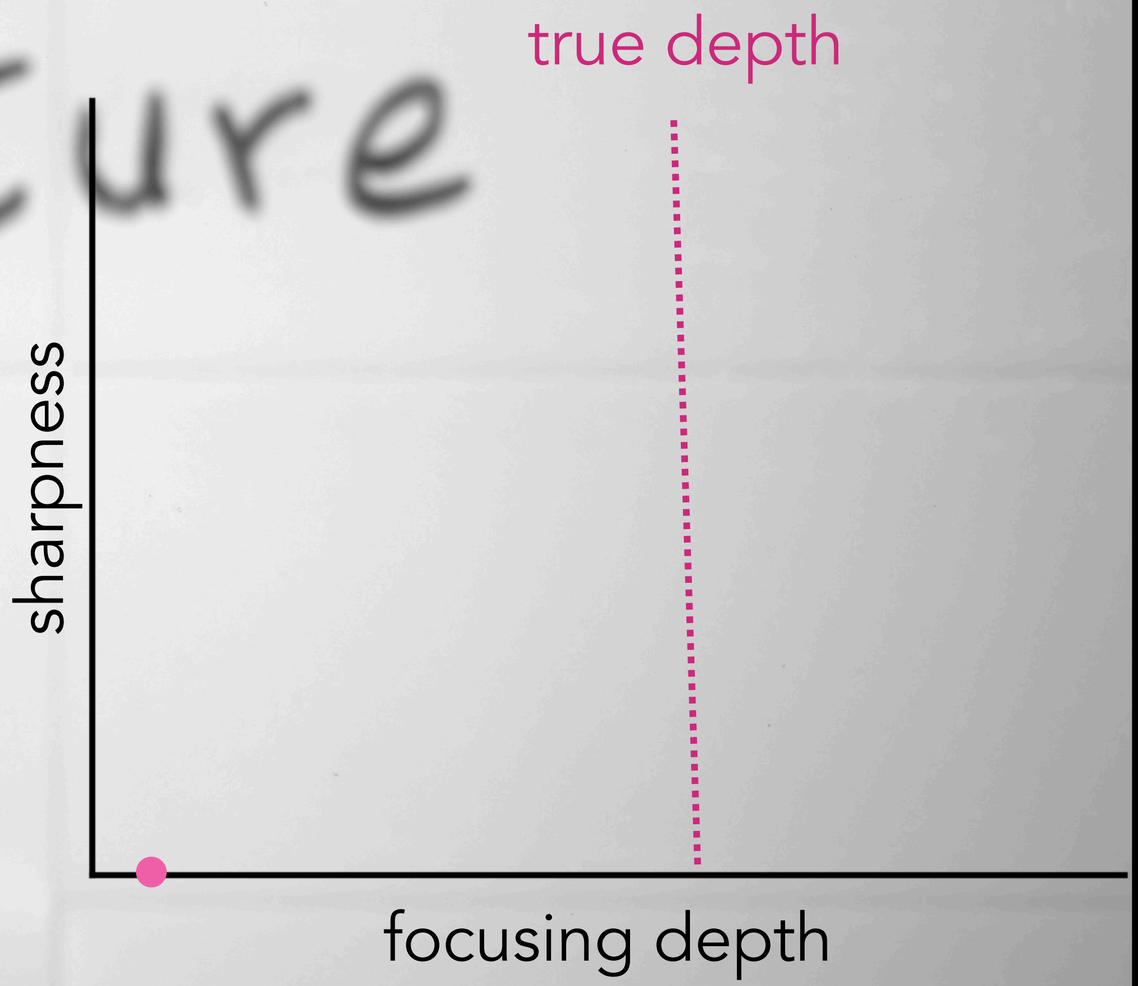

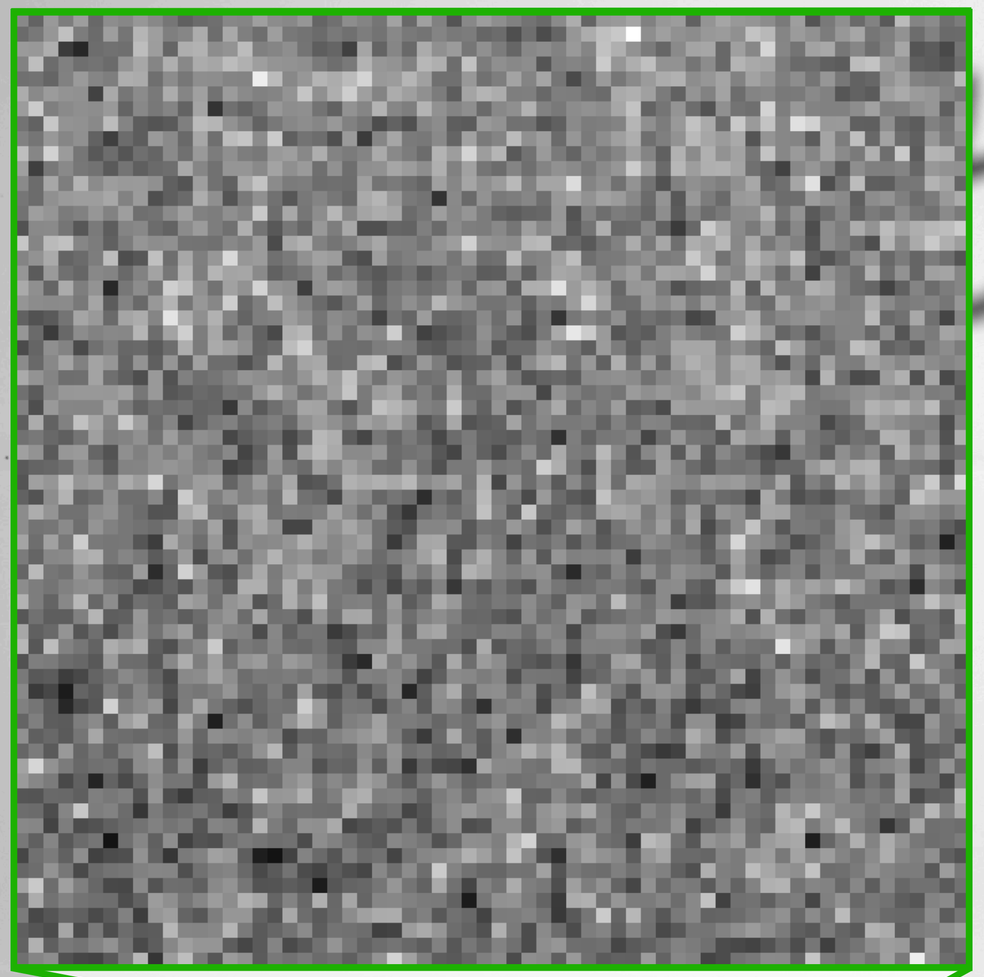

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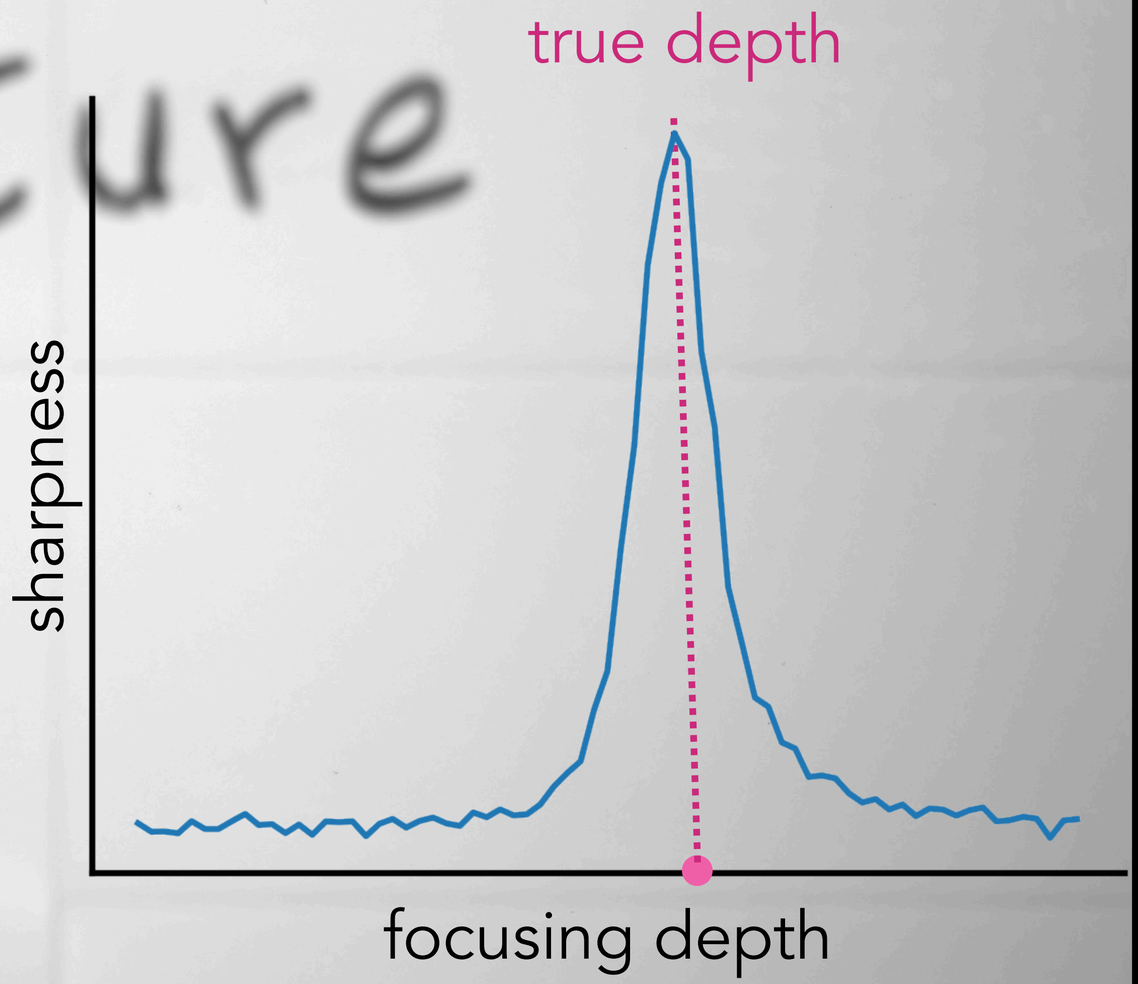

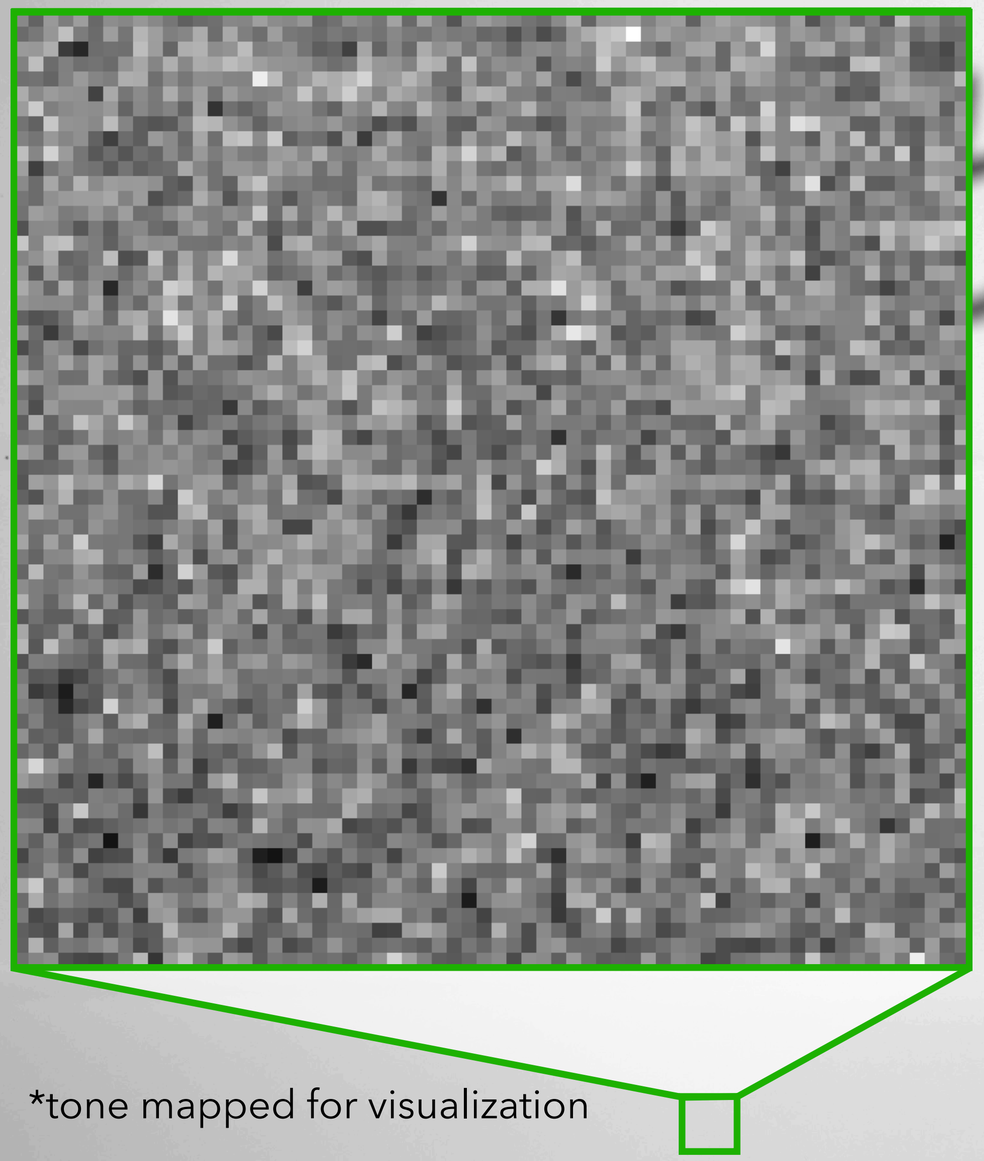

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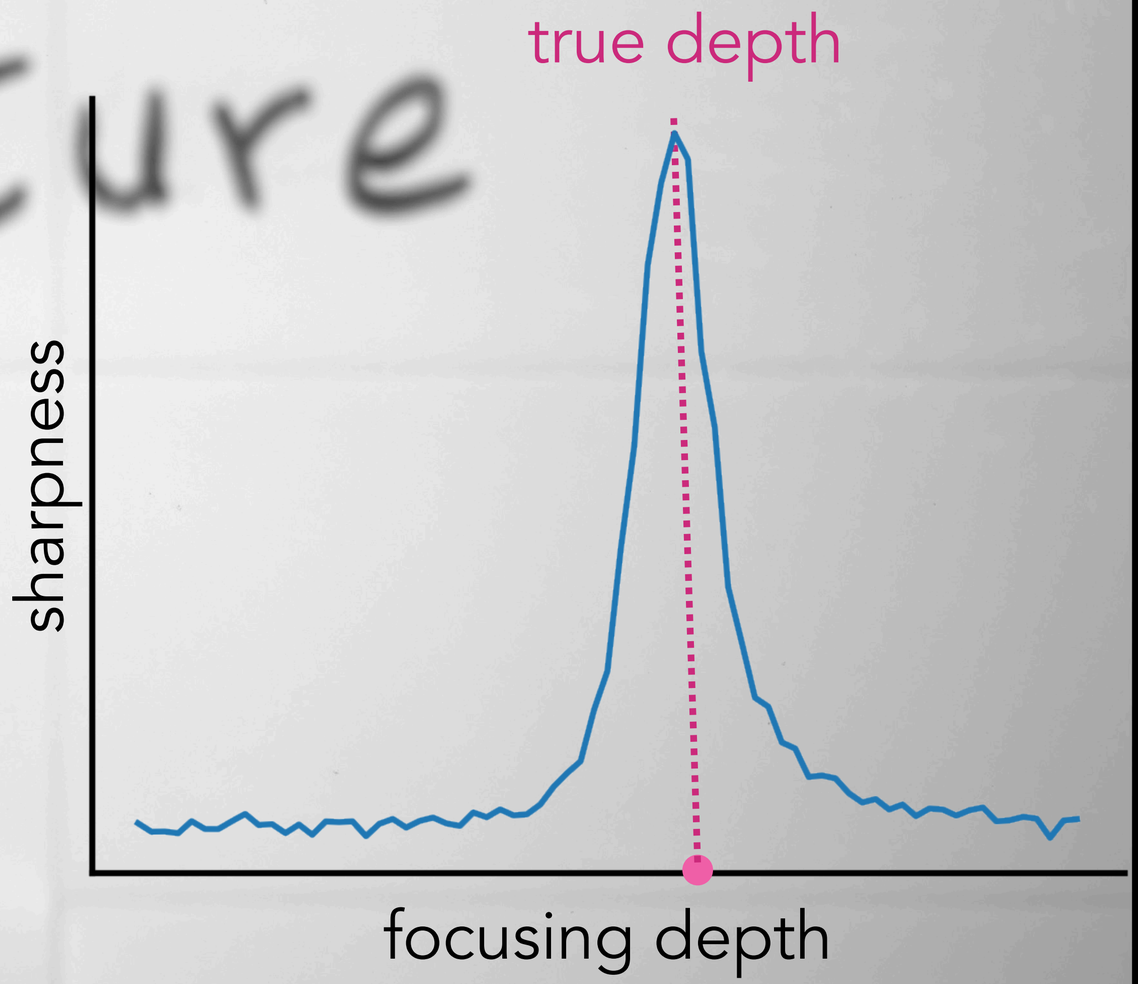

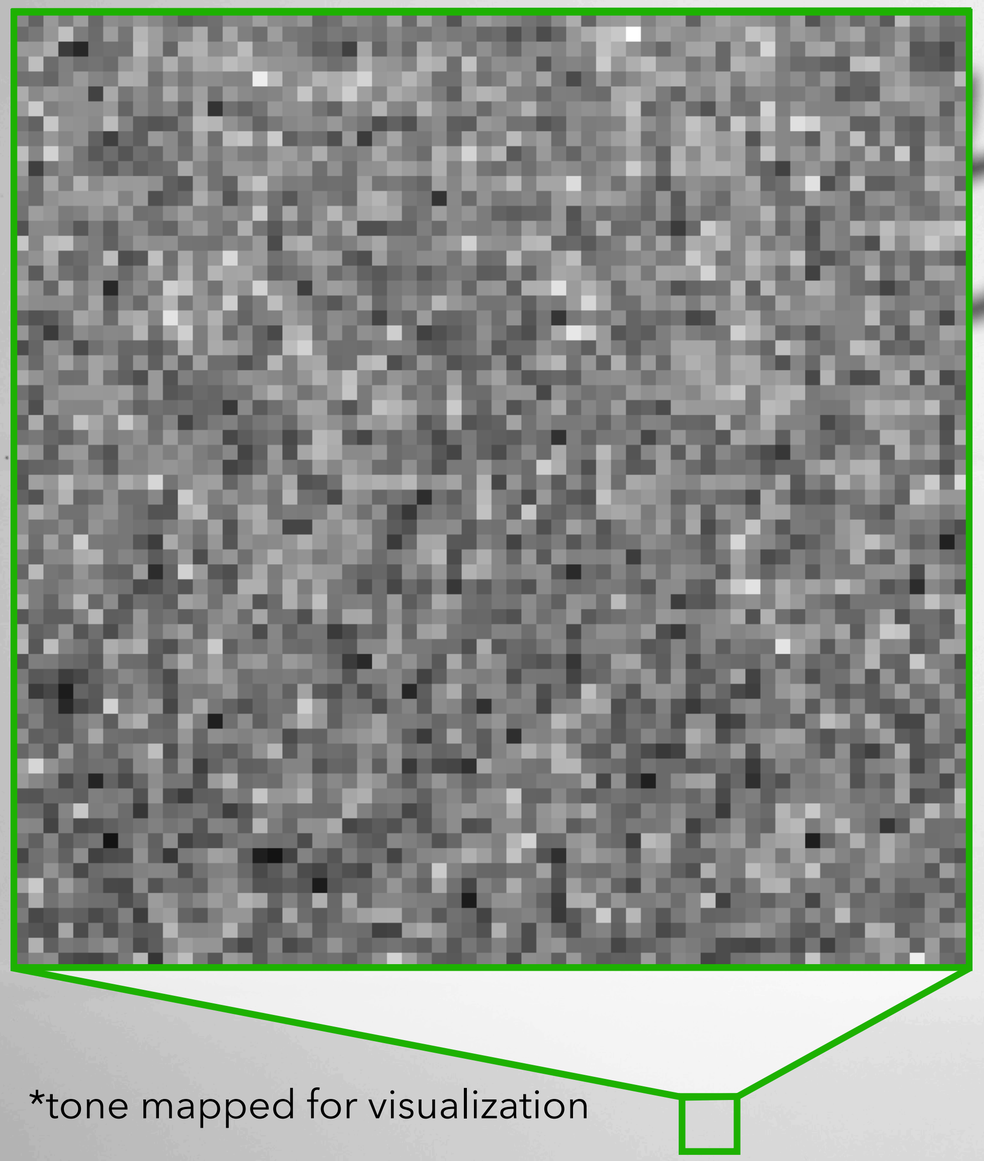

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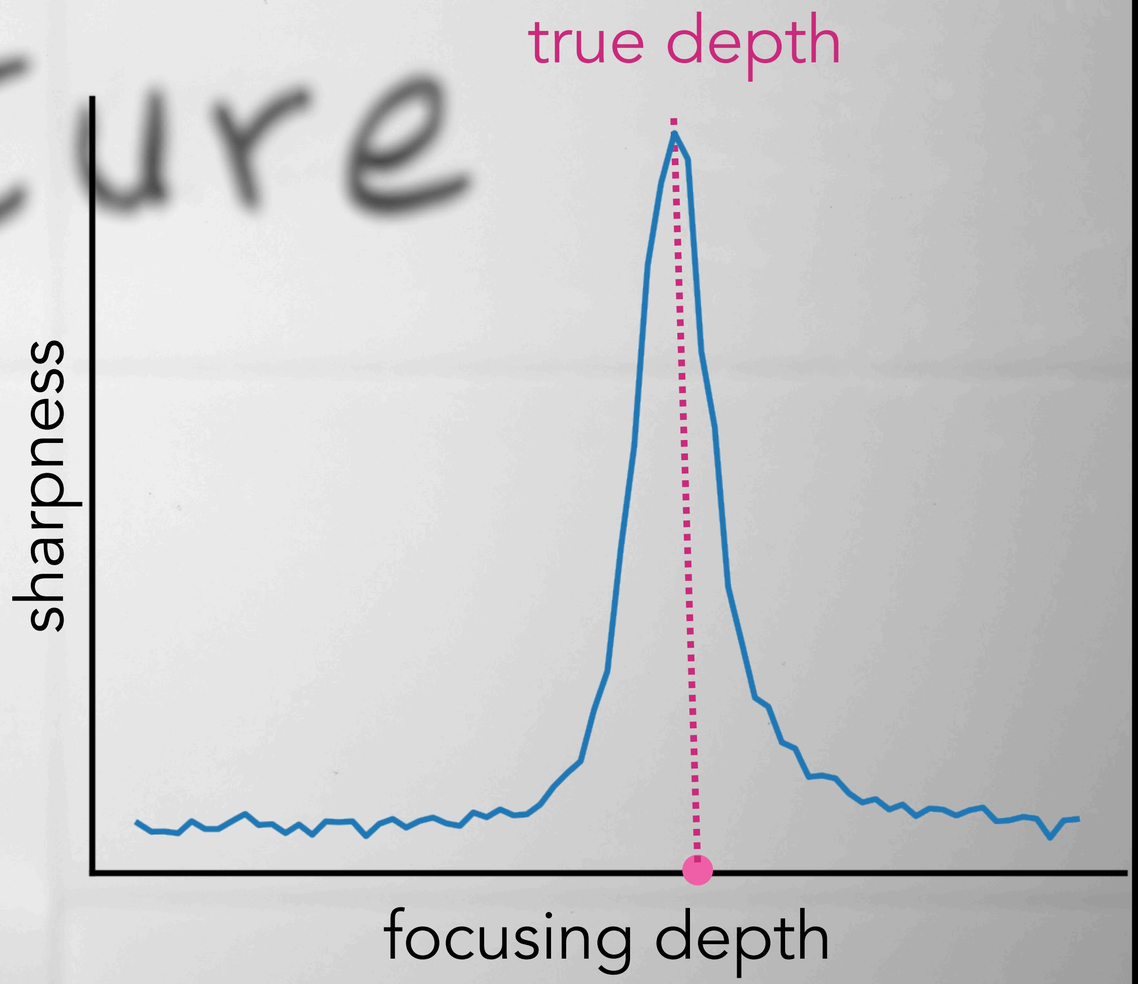

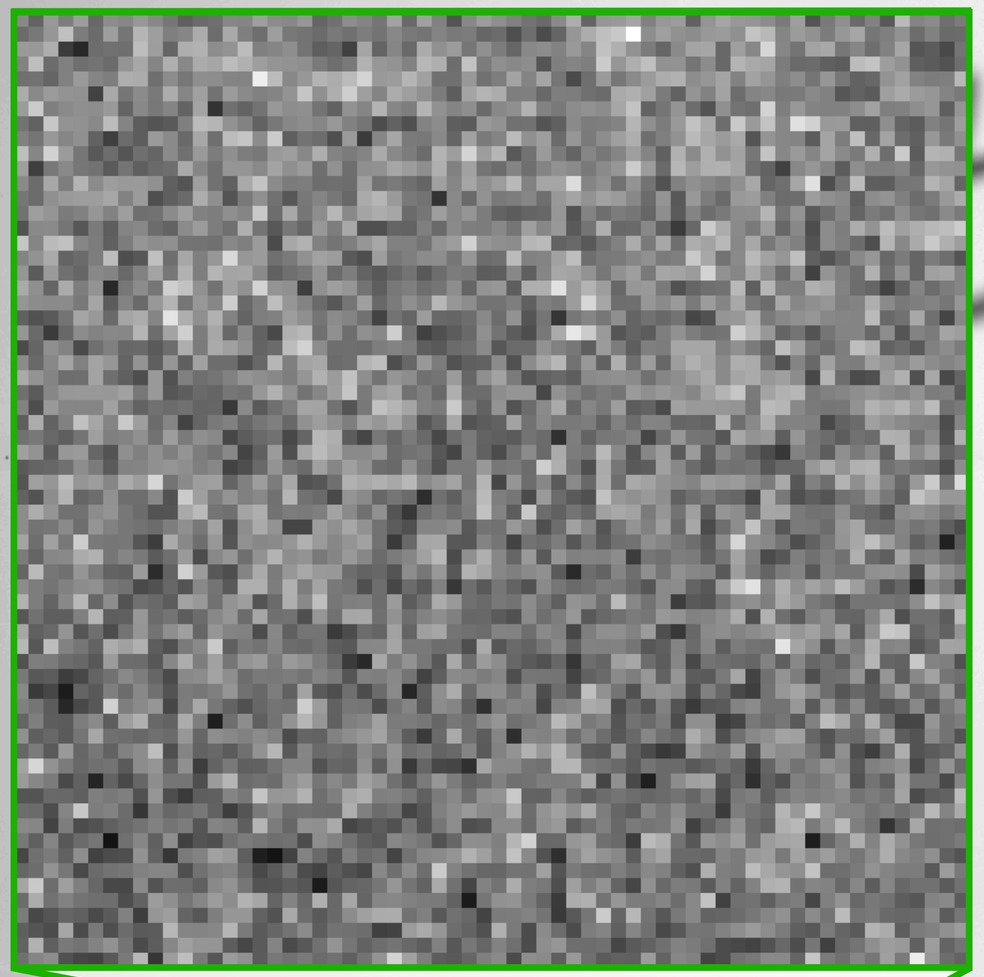

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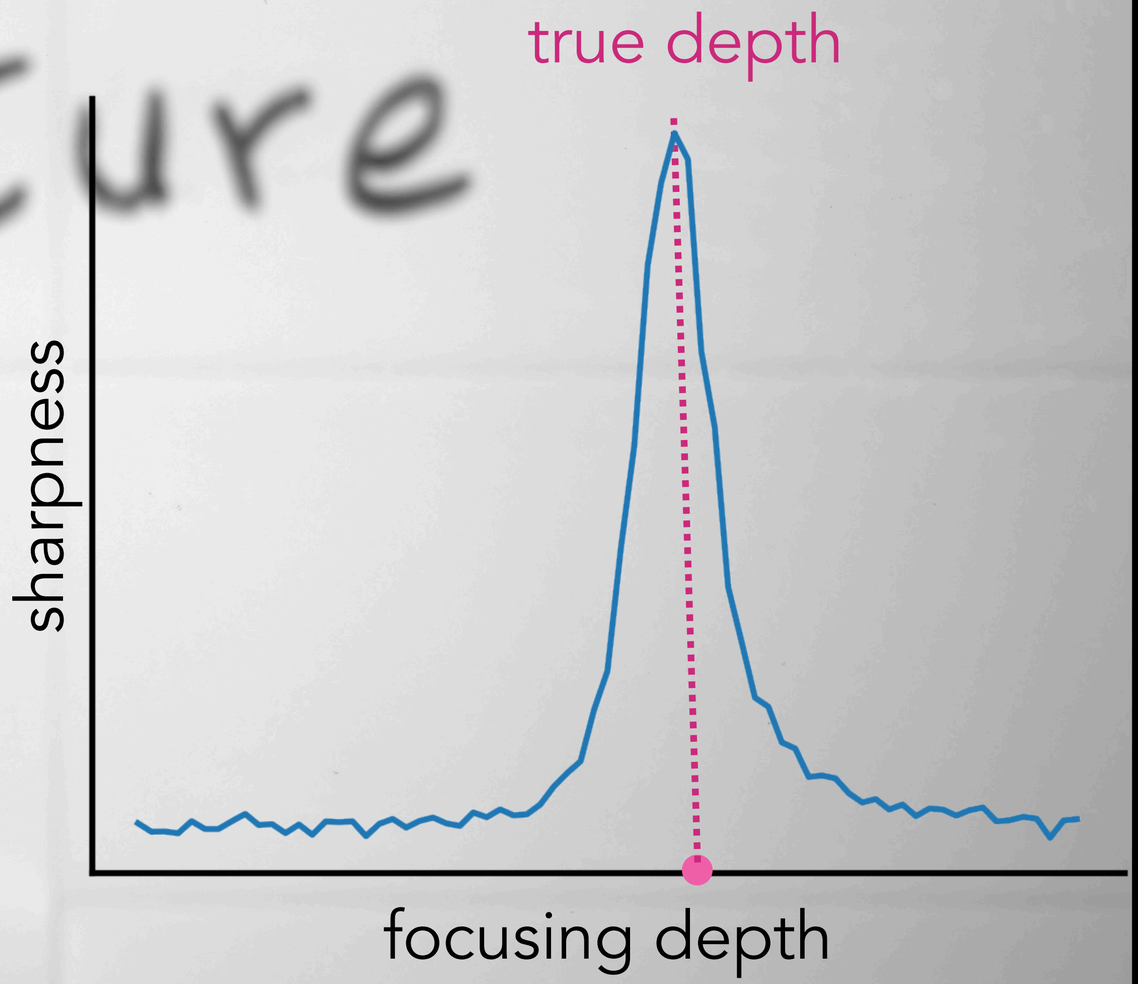

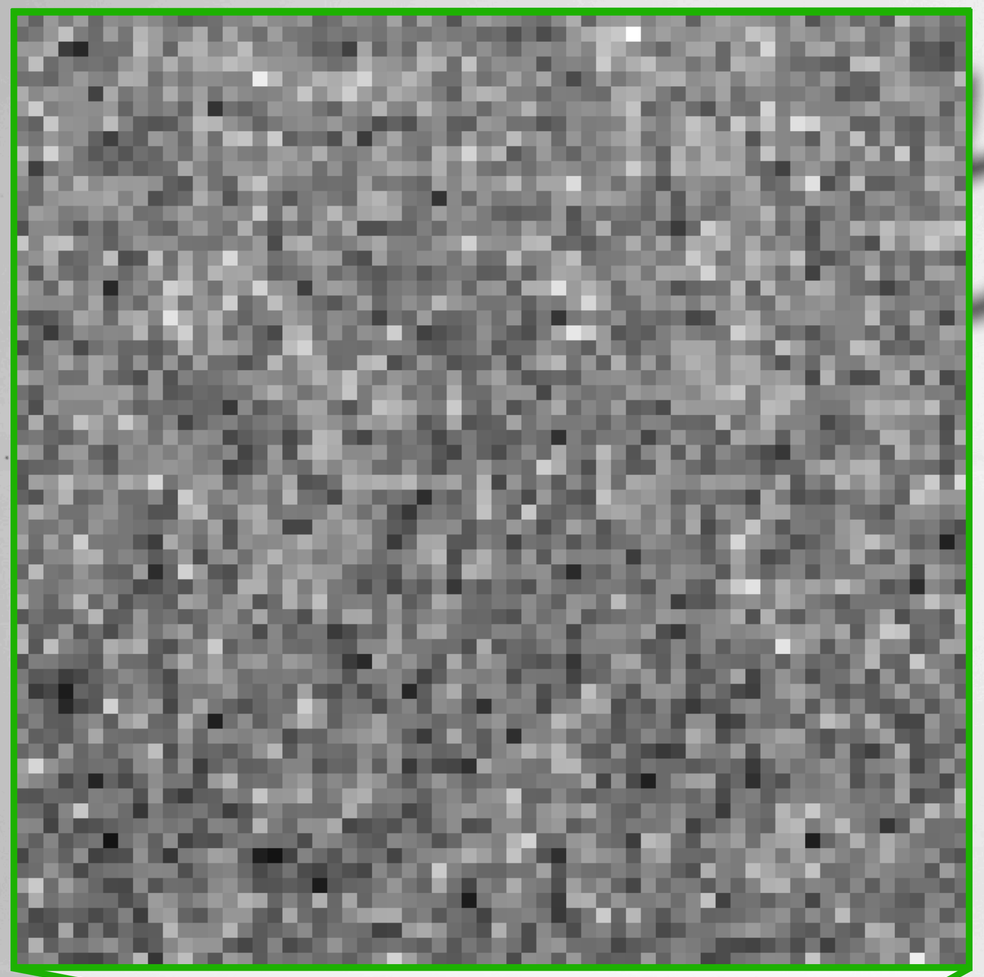

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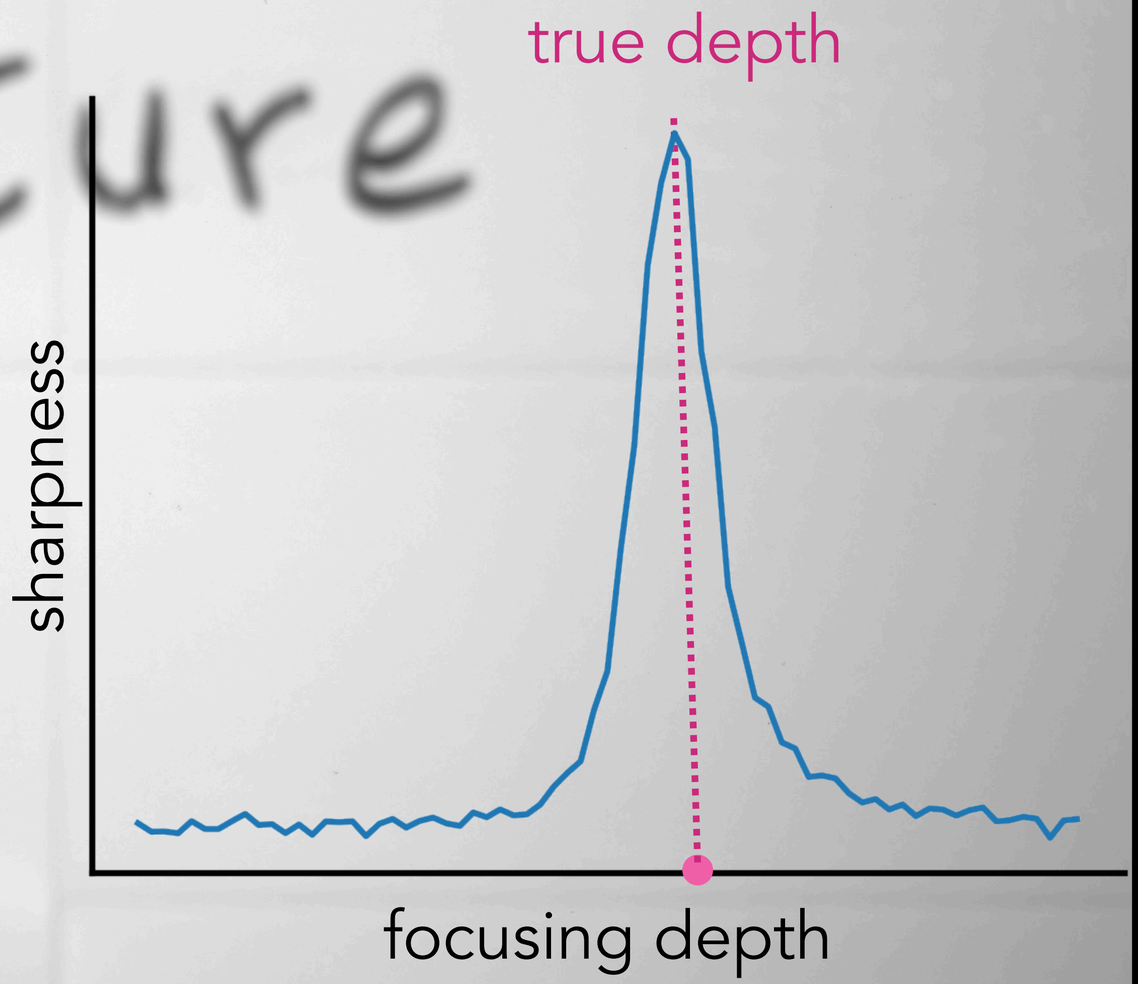

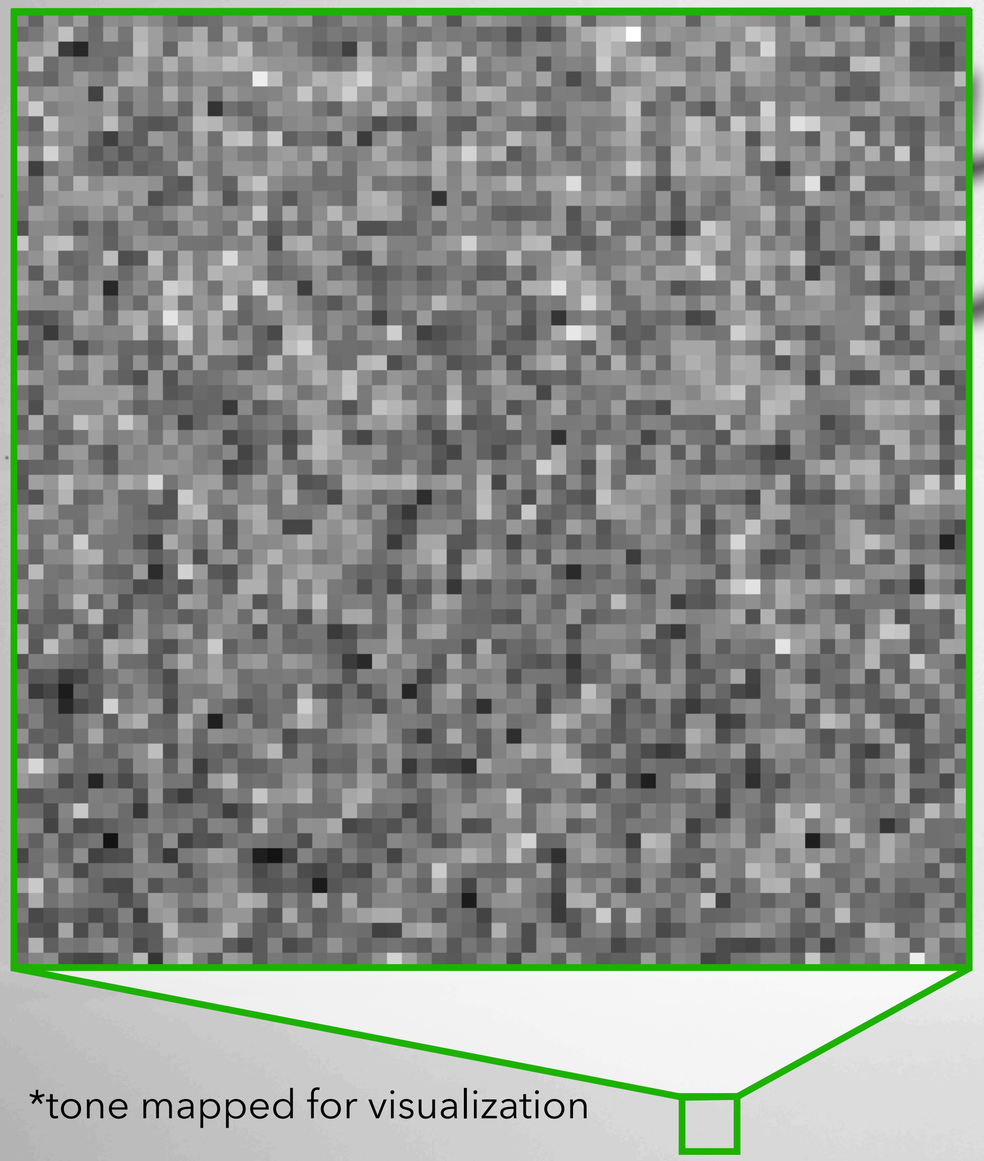

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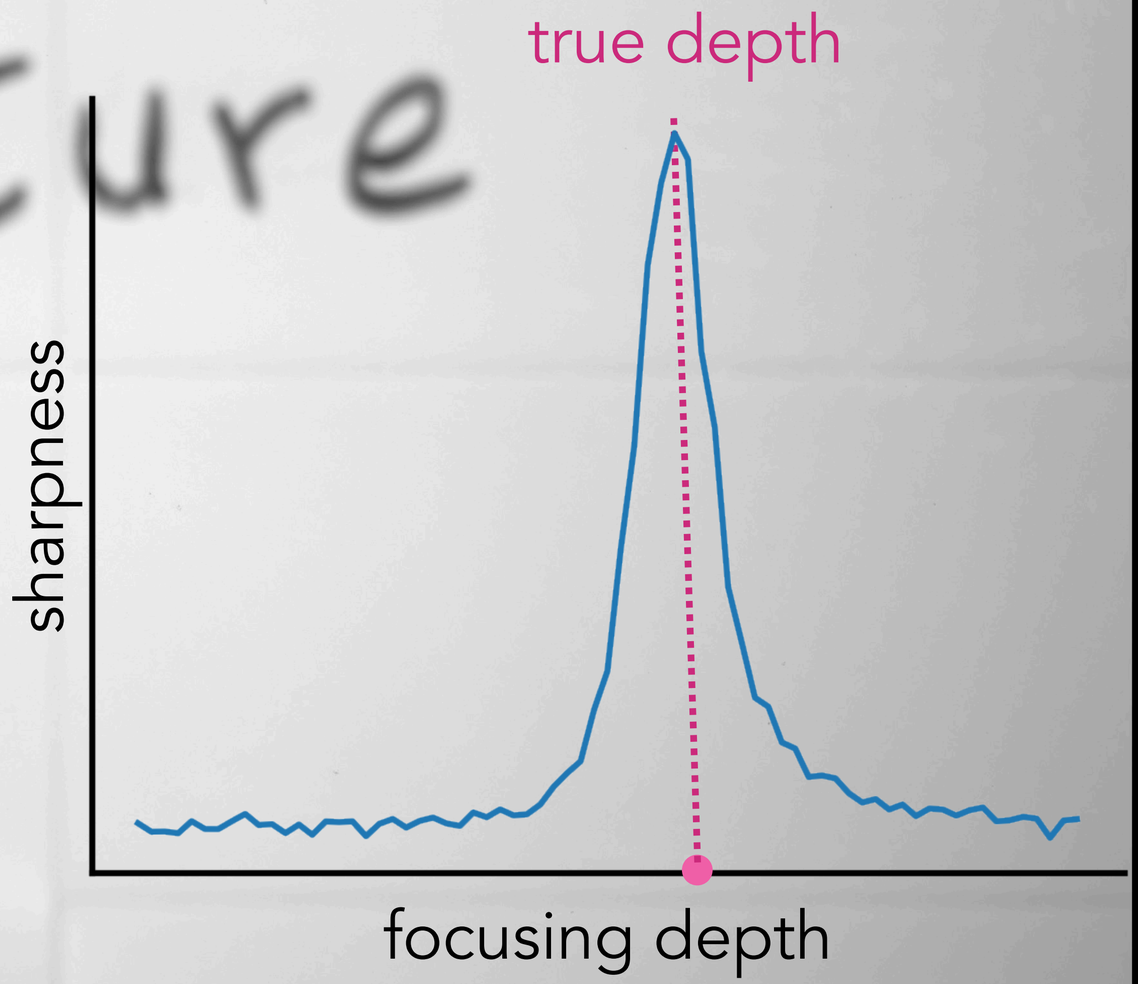
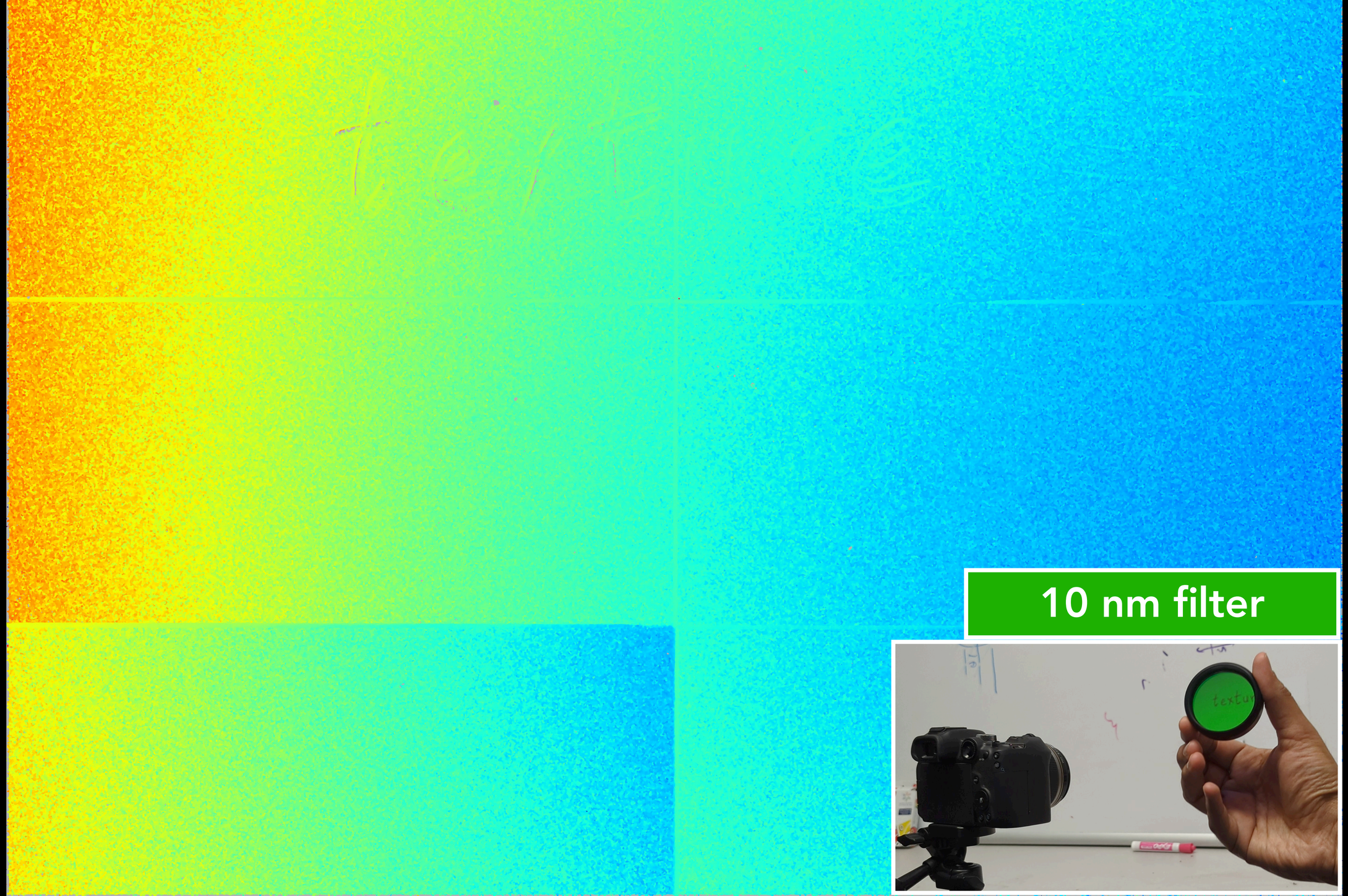


texture

texture
no filter
far
near


10 nm filter
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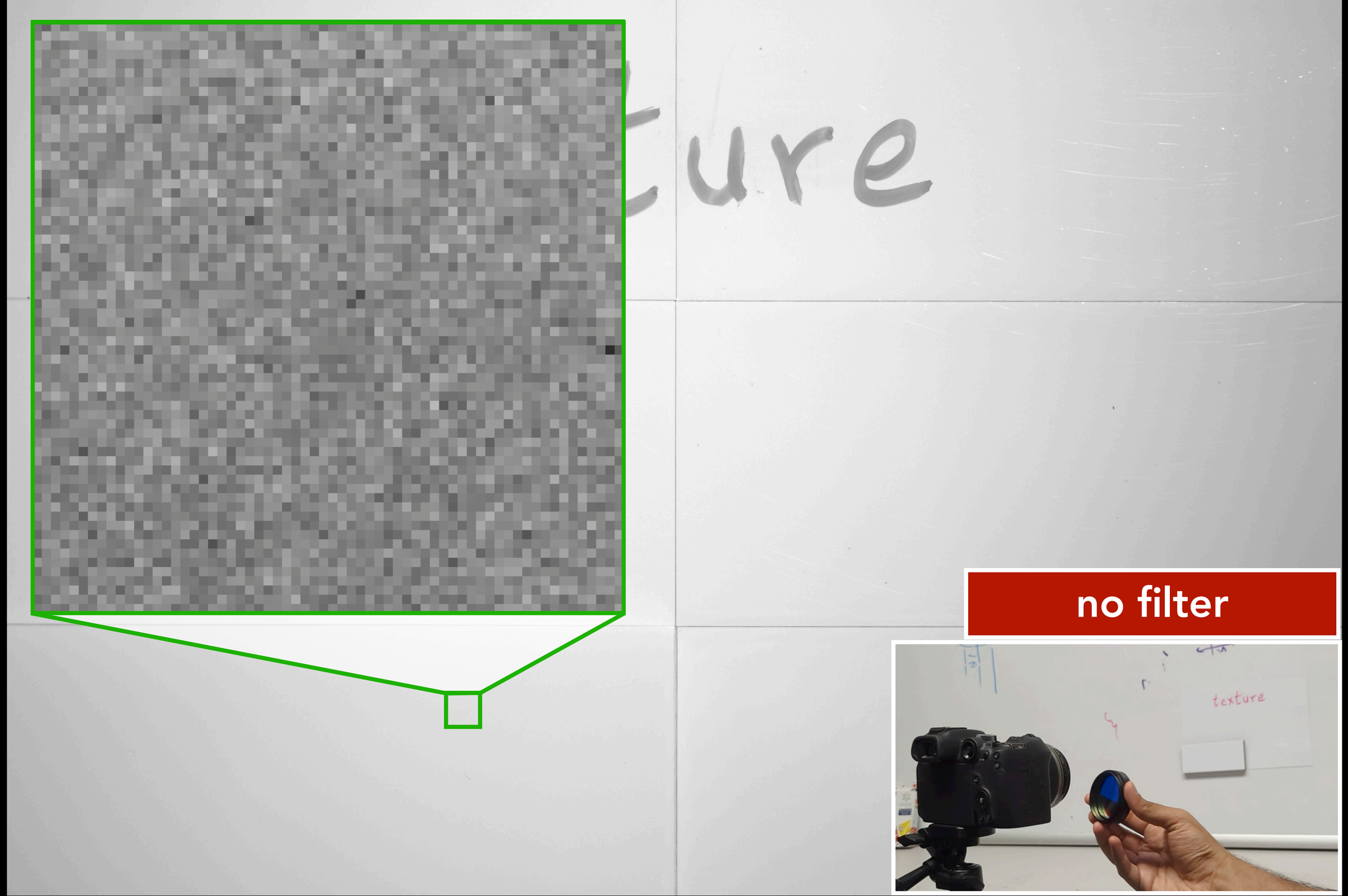
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no filter
texture
far
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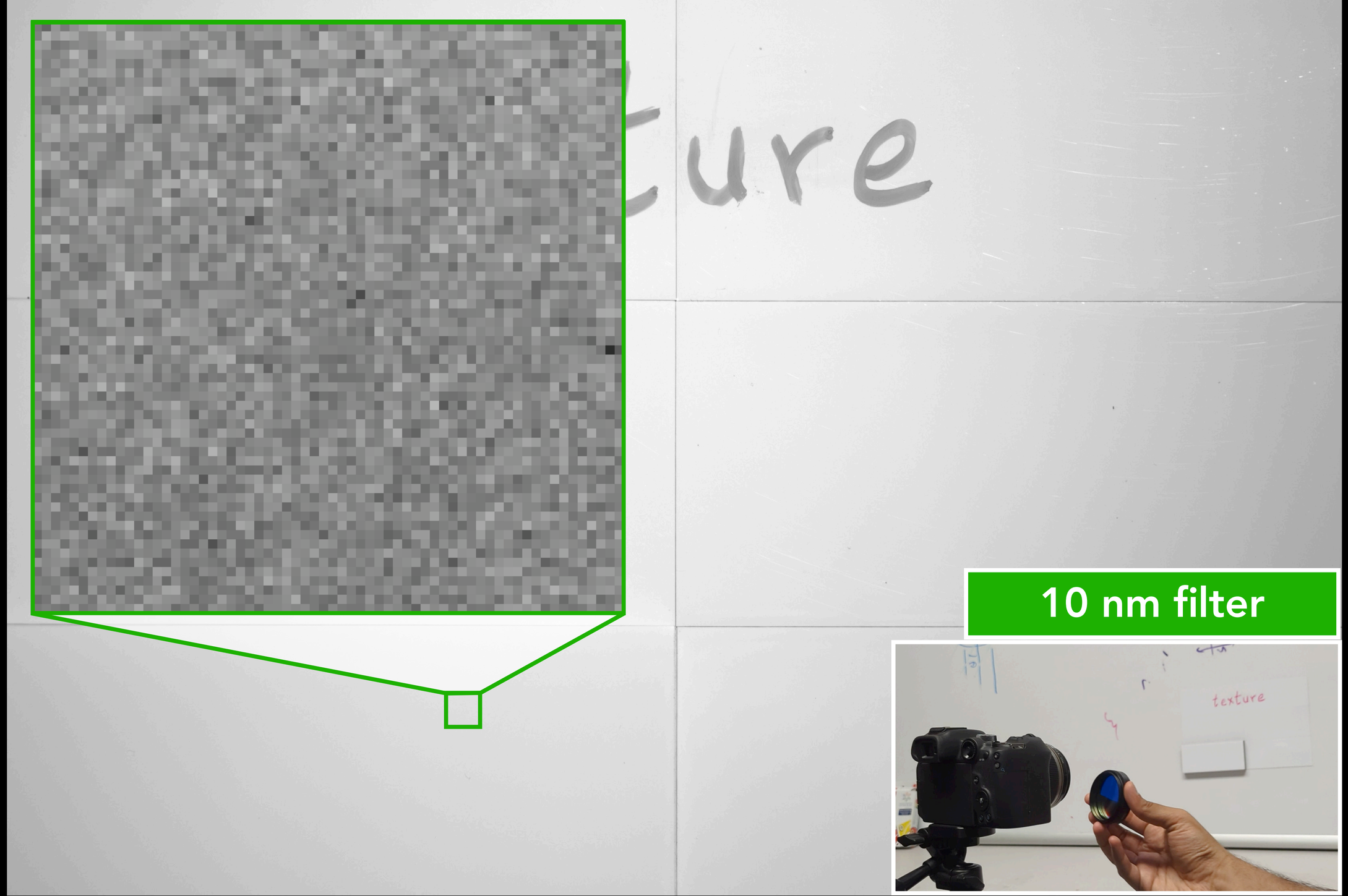
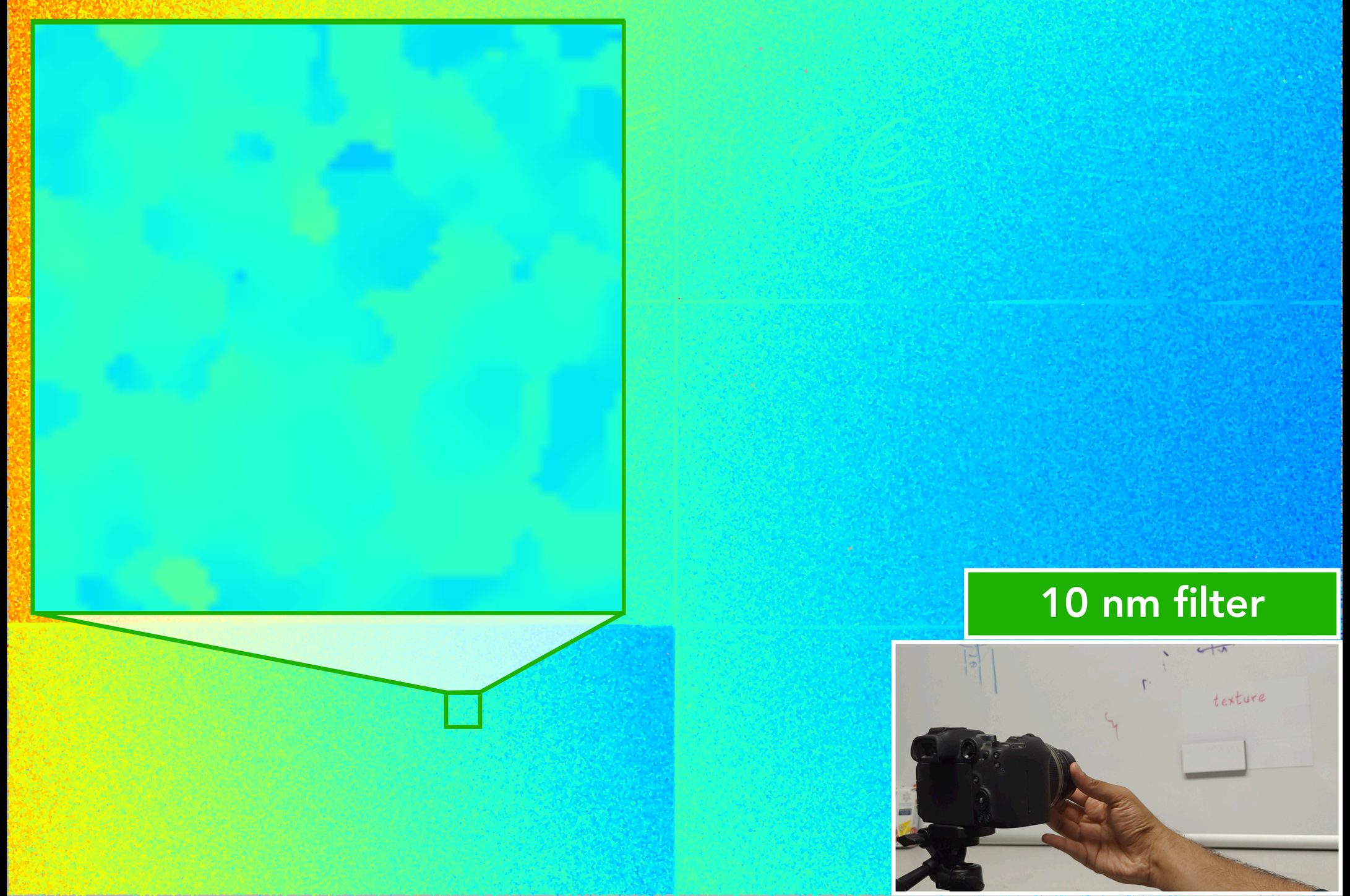

10 nm filter
texture
far
near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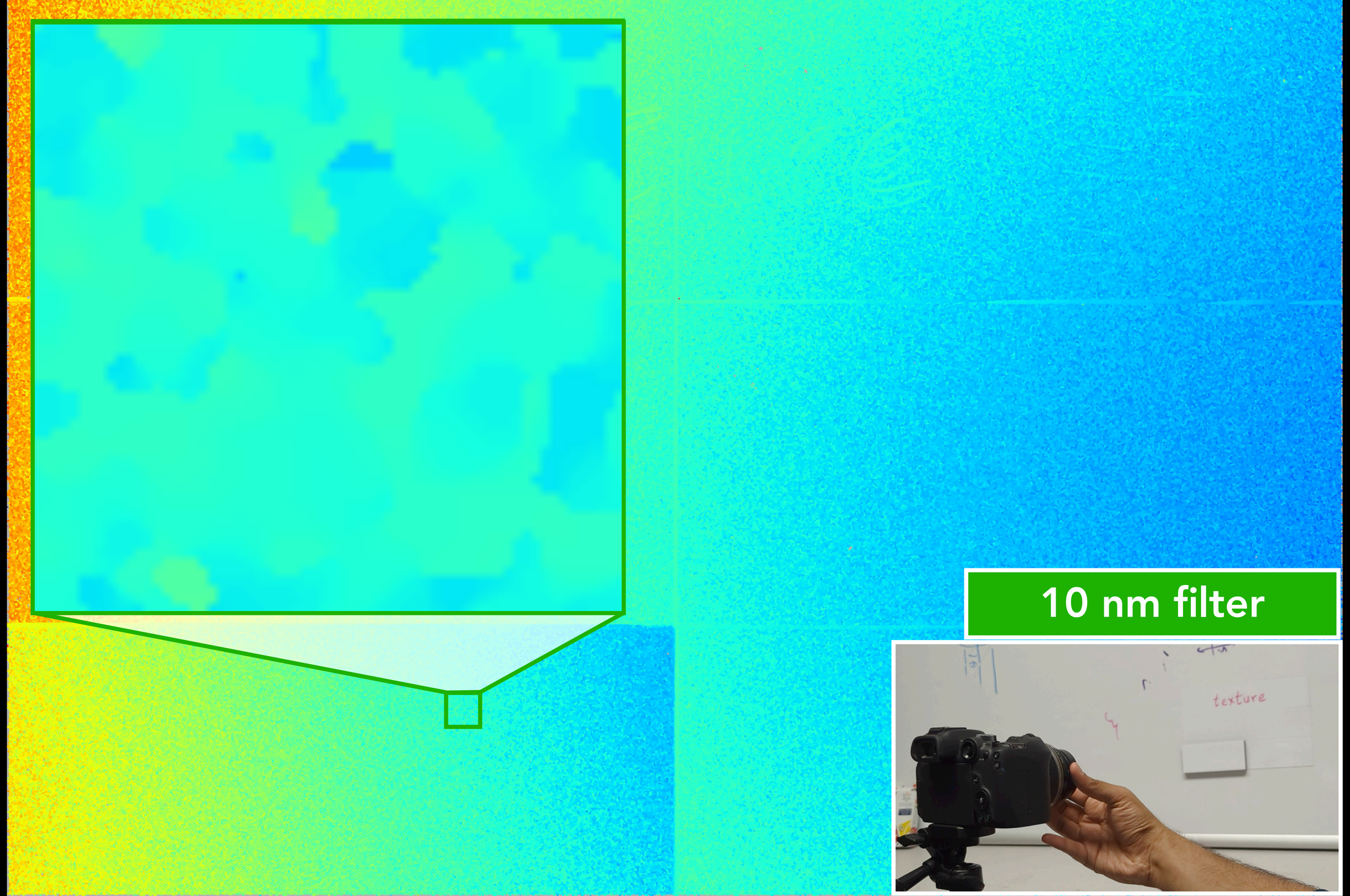
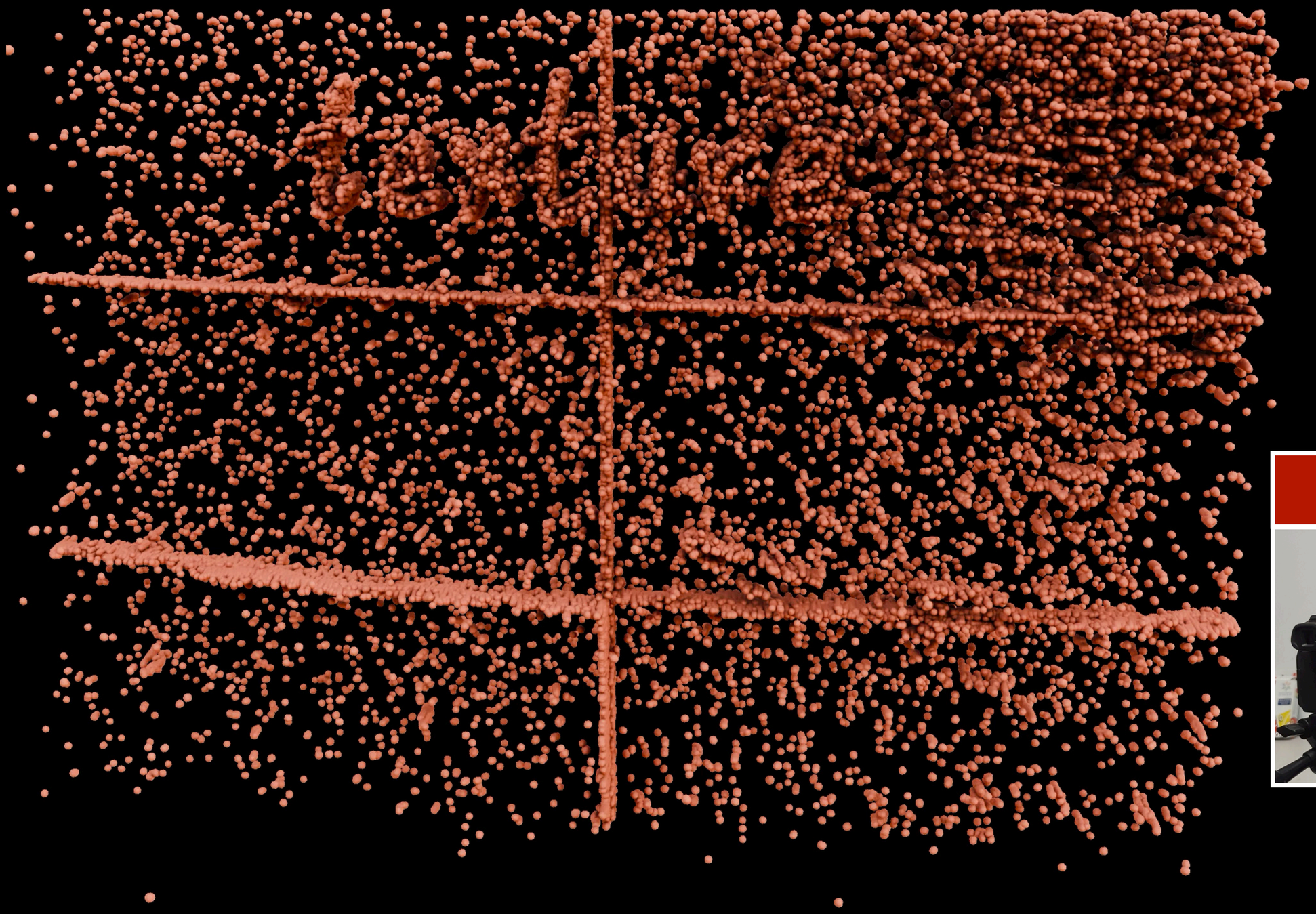
texture
far
near


10 nm filter
texture
far
near



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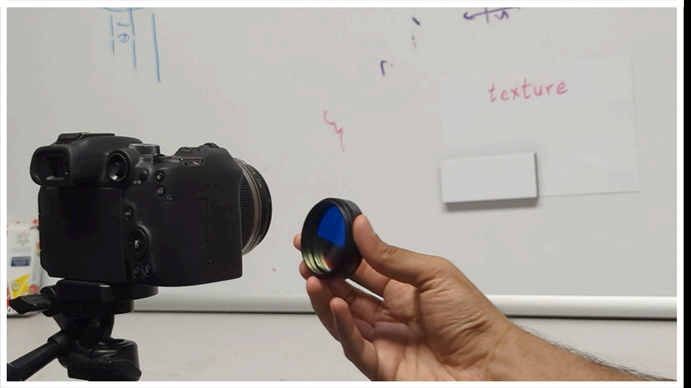
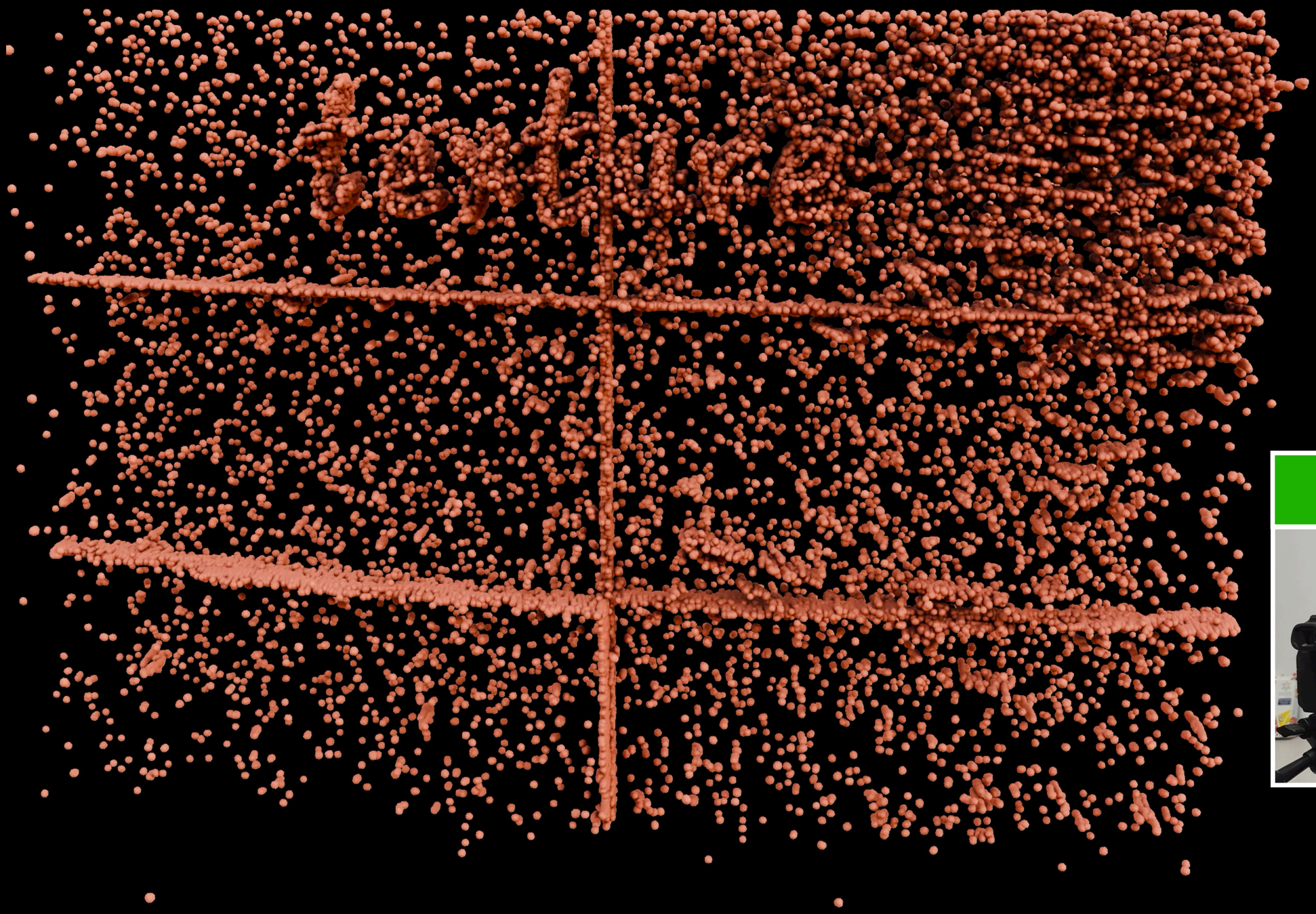
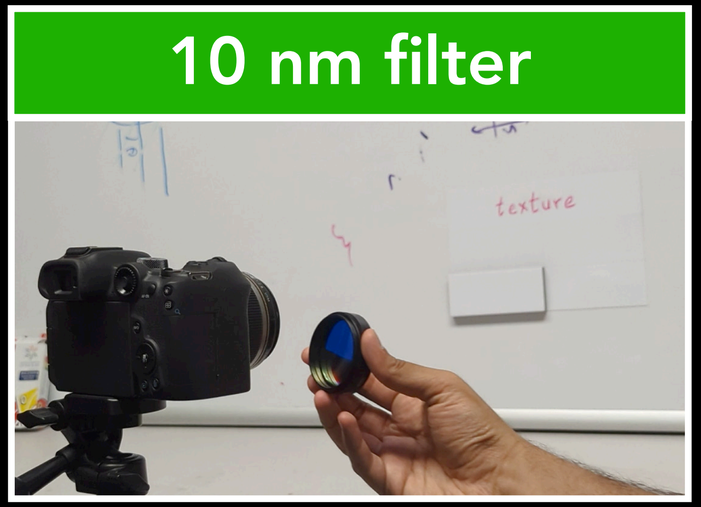
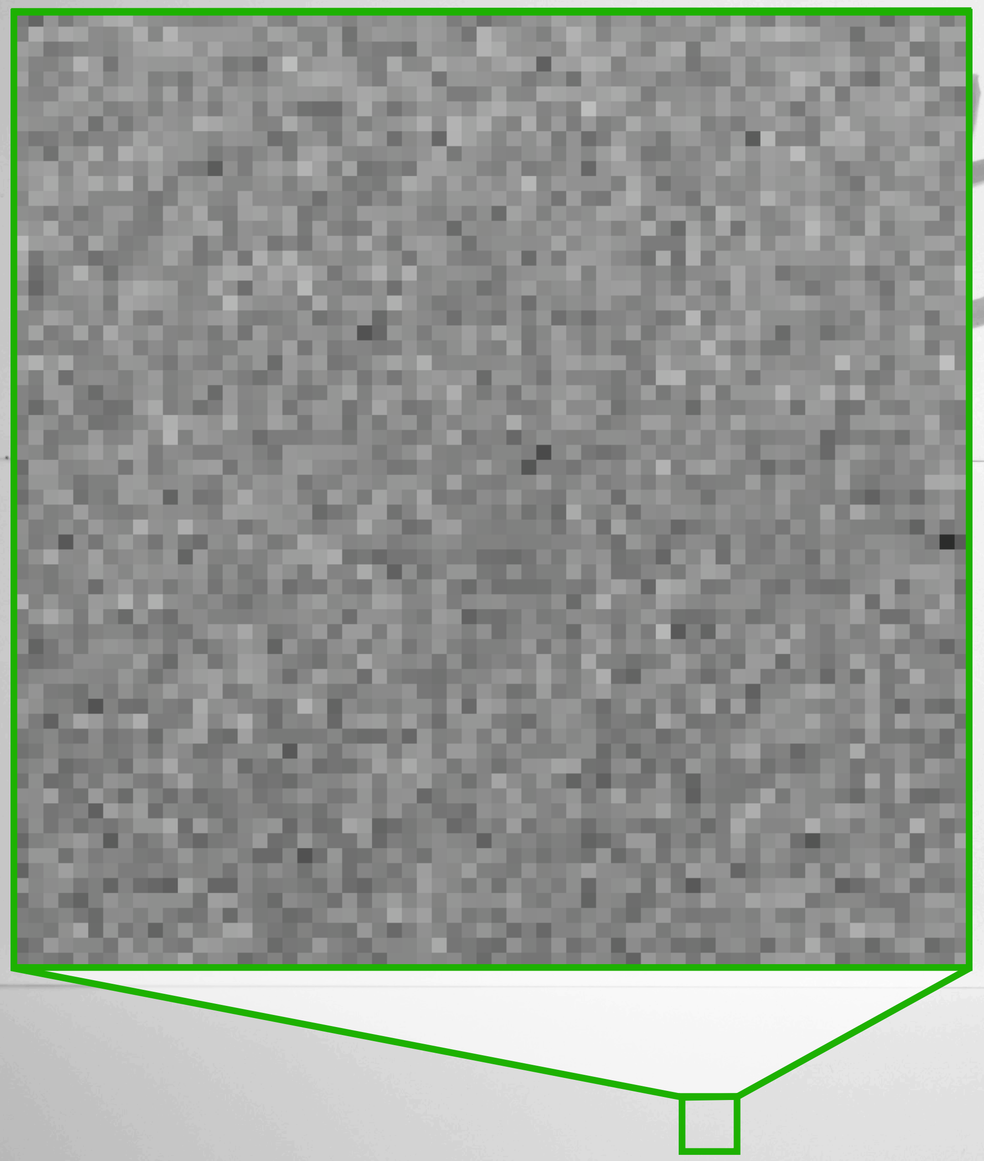
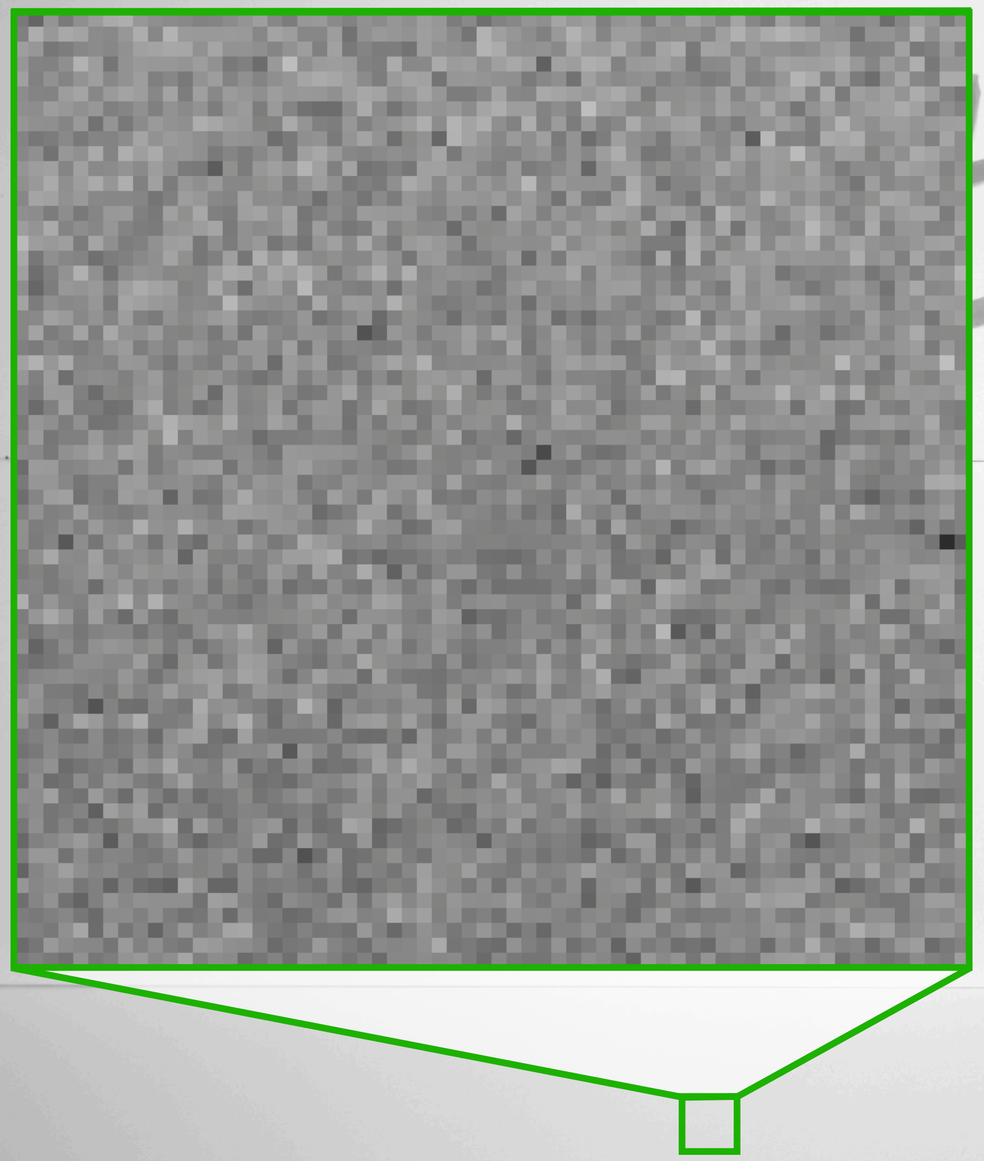


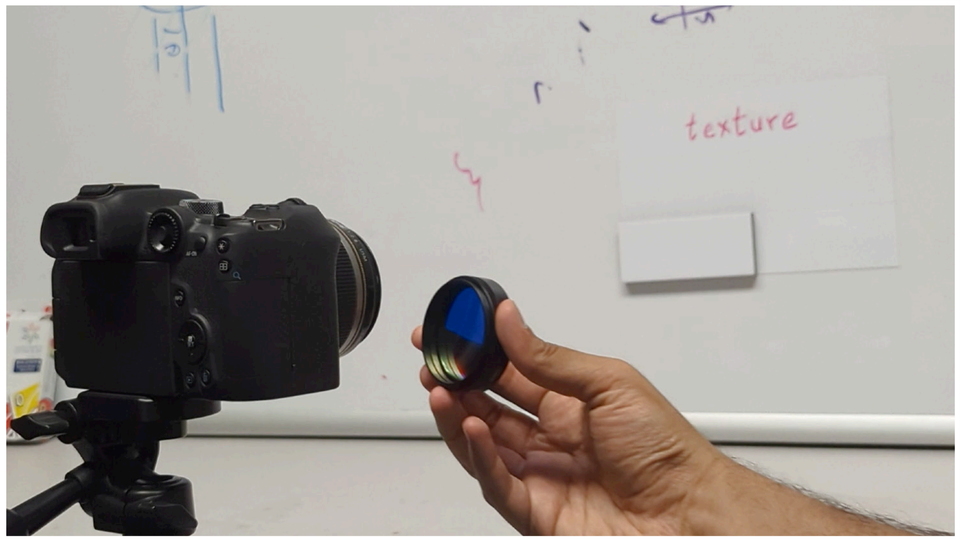



10 nm filter
texture



texture

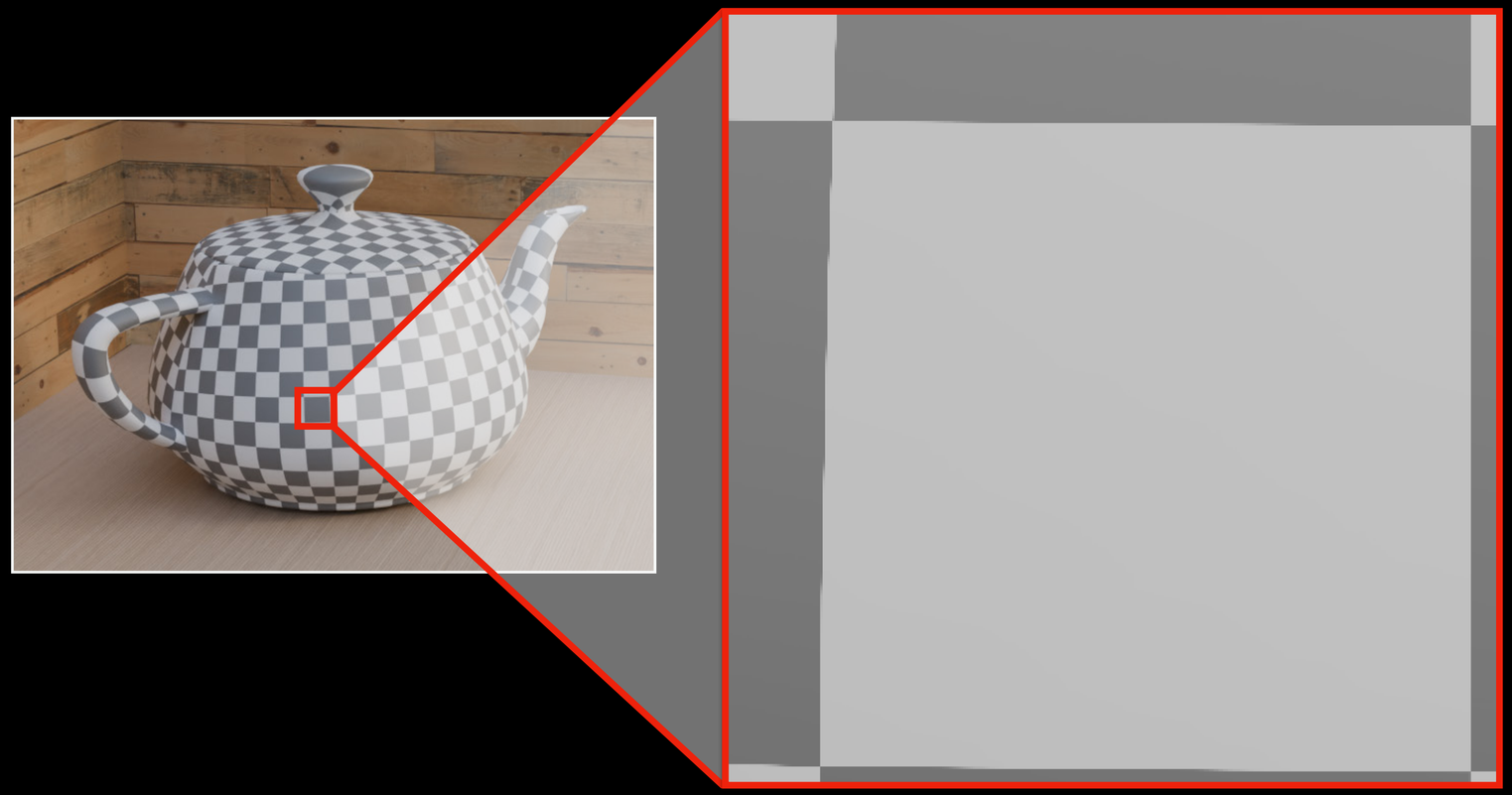




What causes this
noise-like texture?

a new form of texture

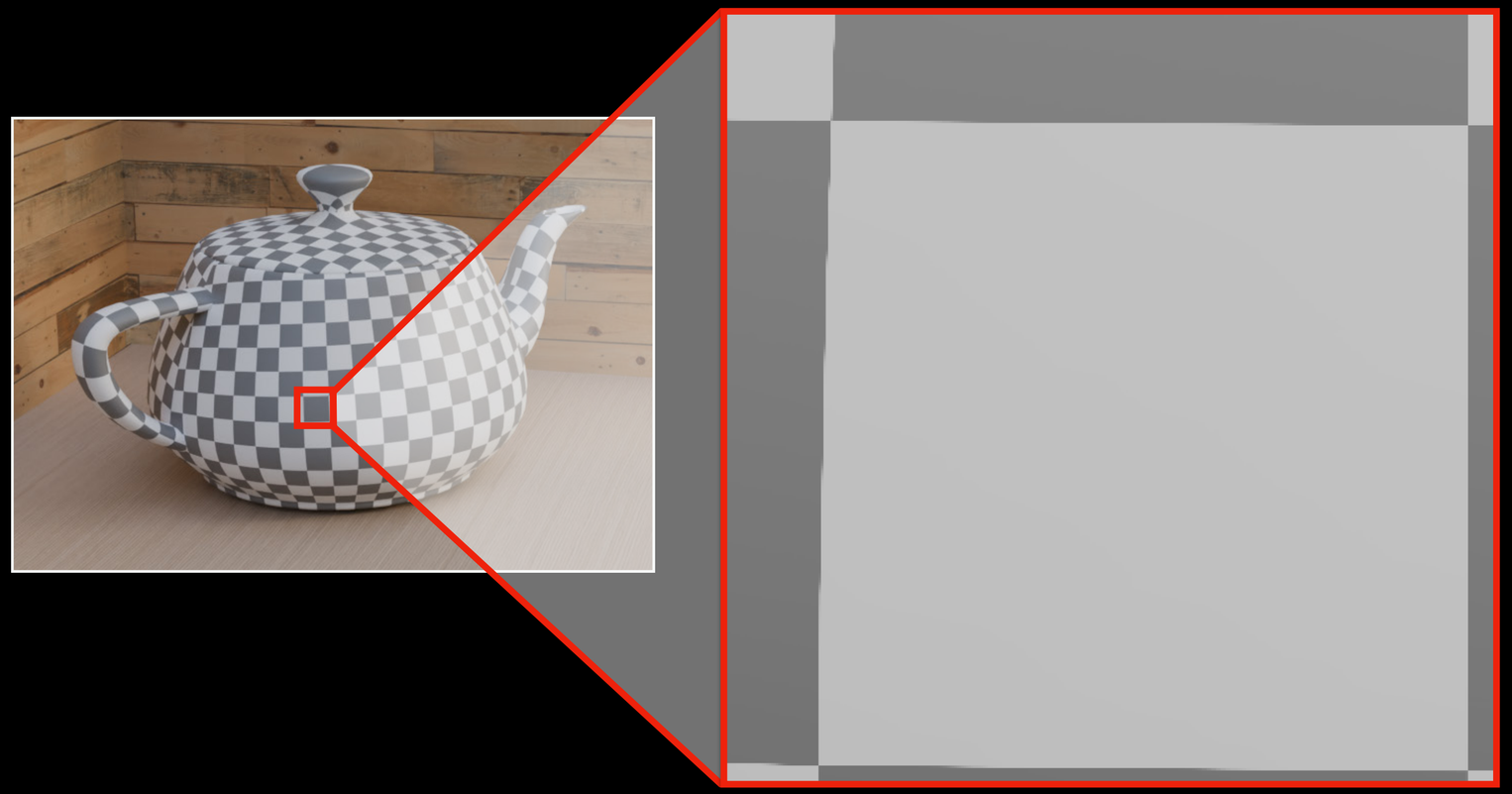
classical texture



spatial variation
of albedo (BRDF)

a new form of texture

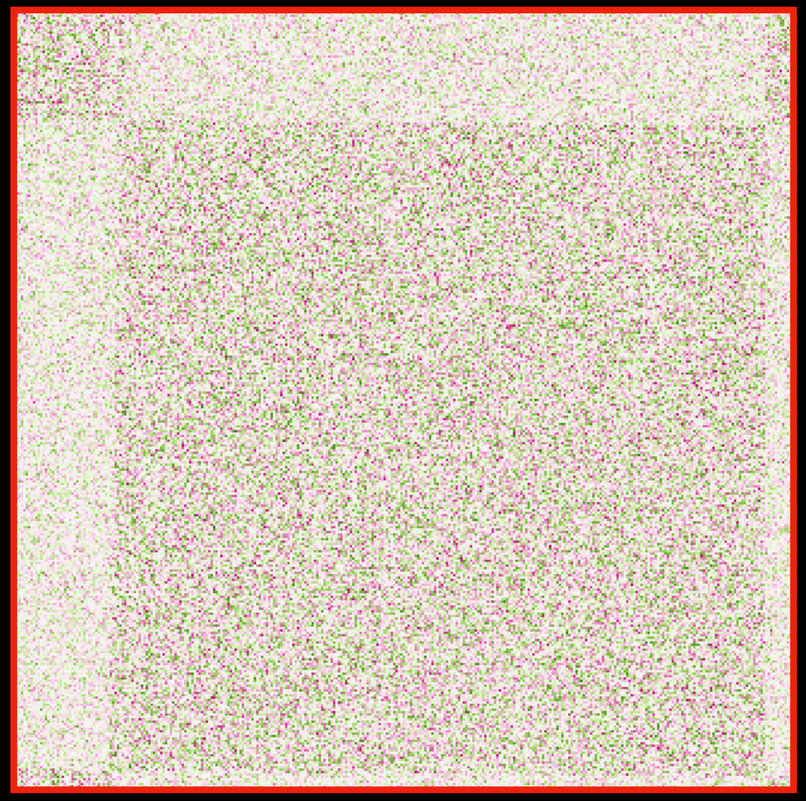
classical texture



spatial variation
of albedo (BRDF)

+

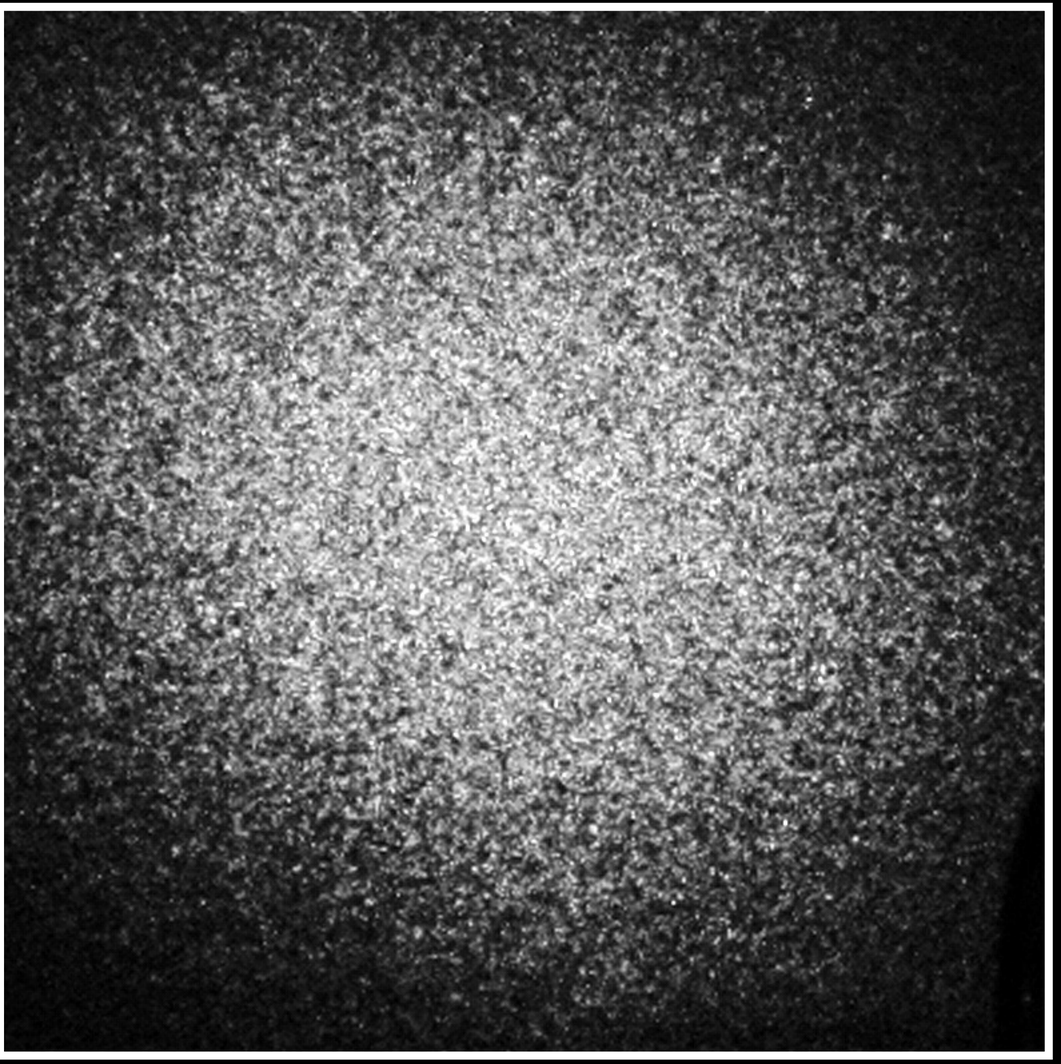
second-order texture



wave-optical
prediction

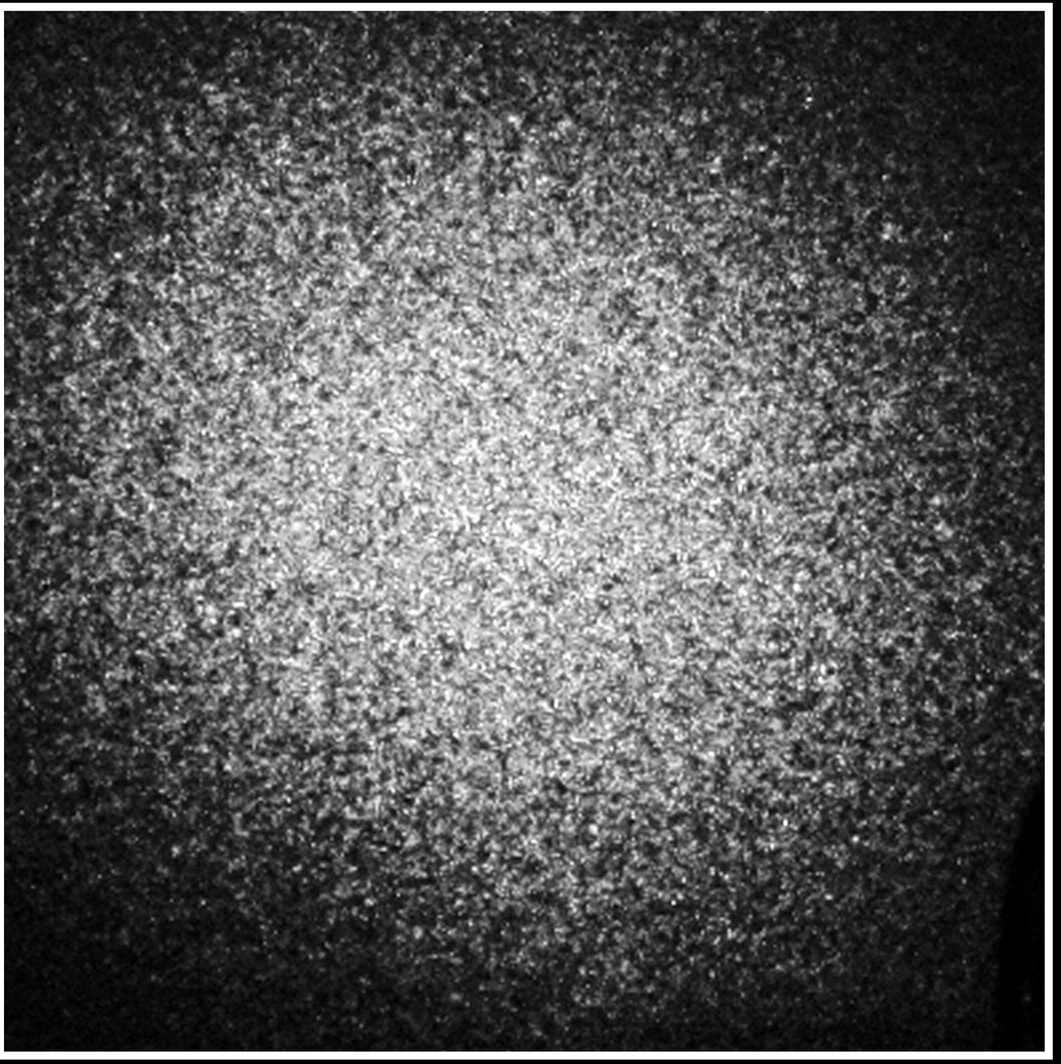
optical speckle

optical speckle



speckle

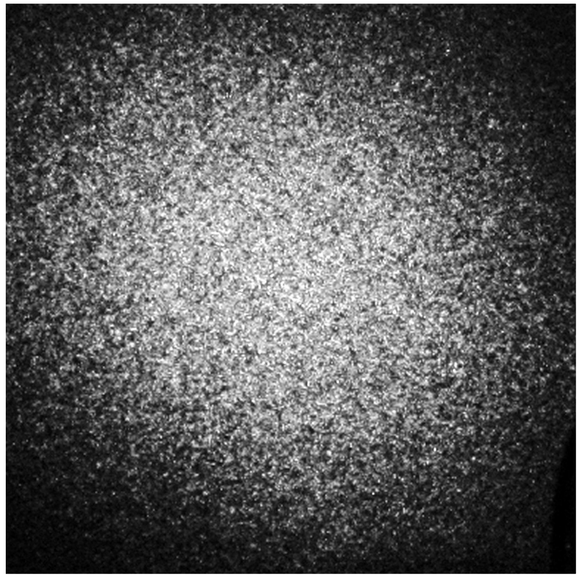
optical speckle

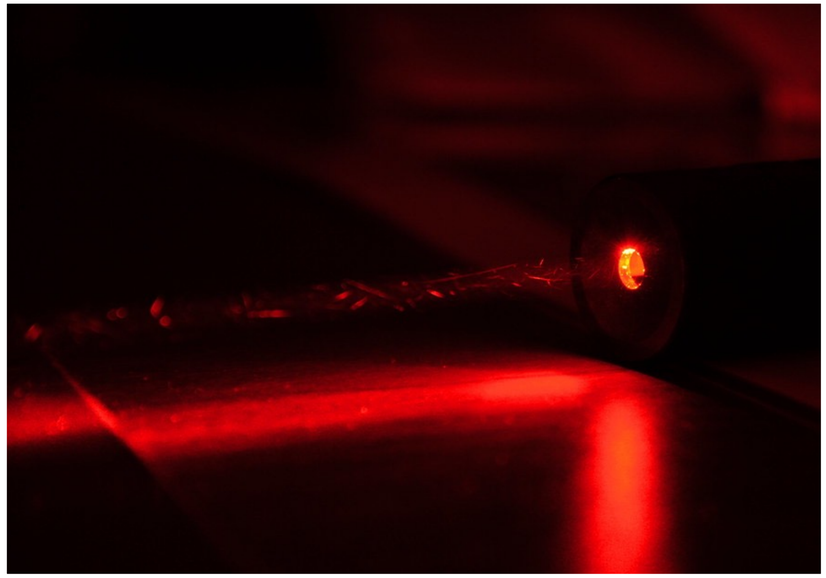


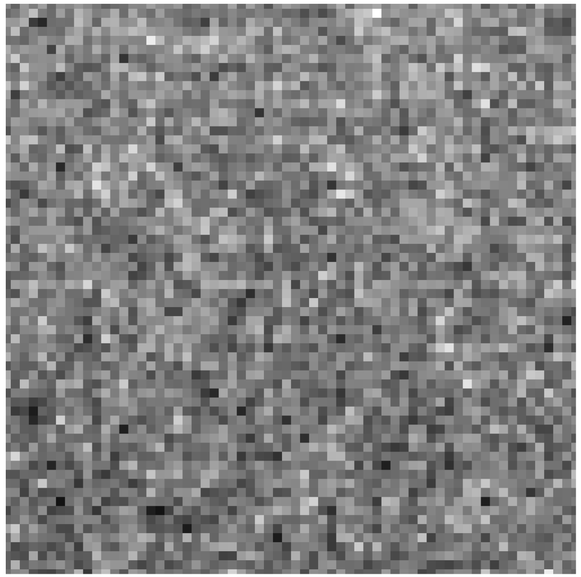
speckle

coherent light (laser)

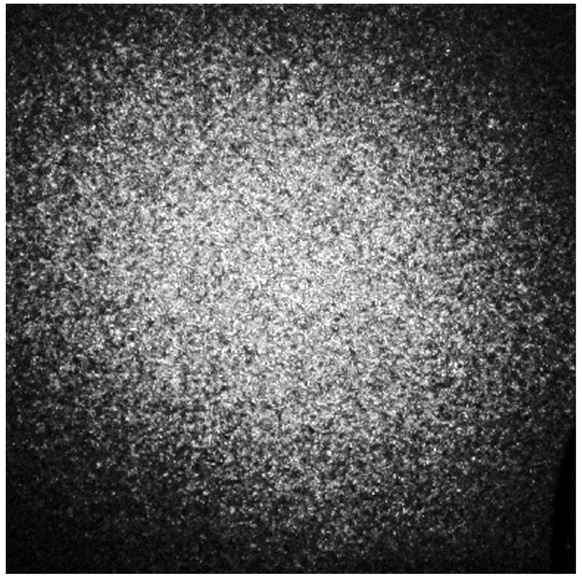
optical speckle

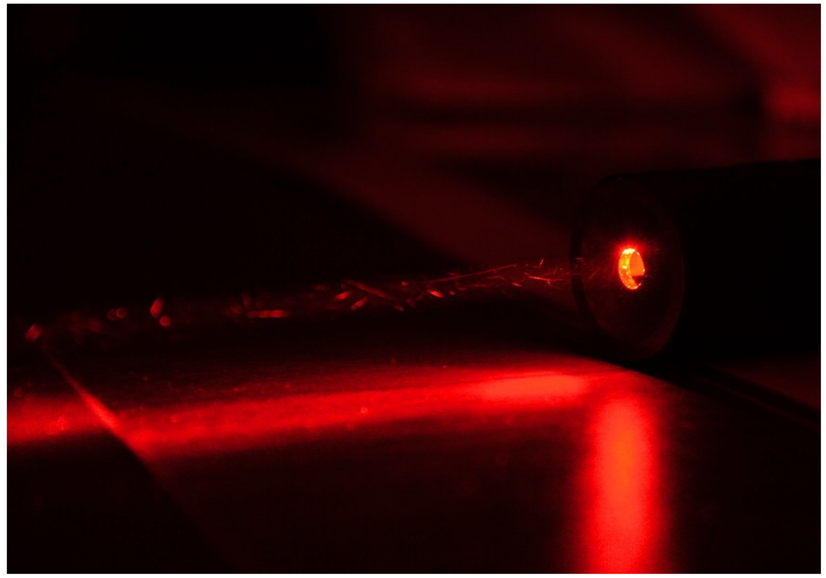




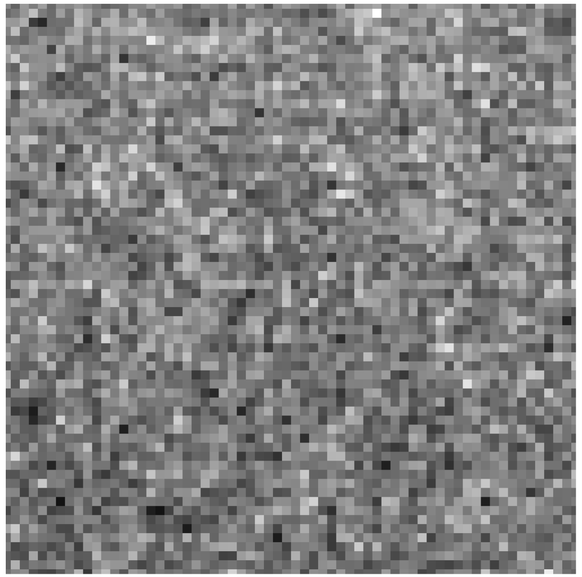


optical speckle



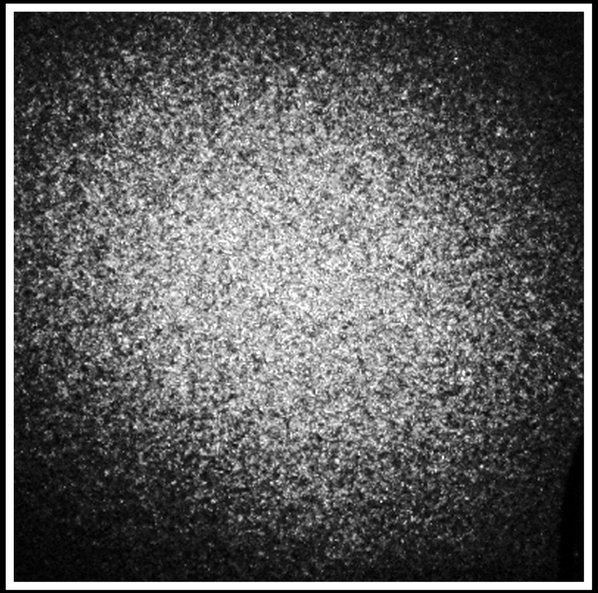


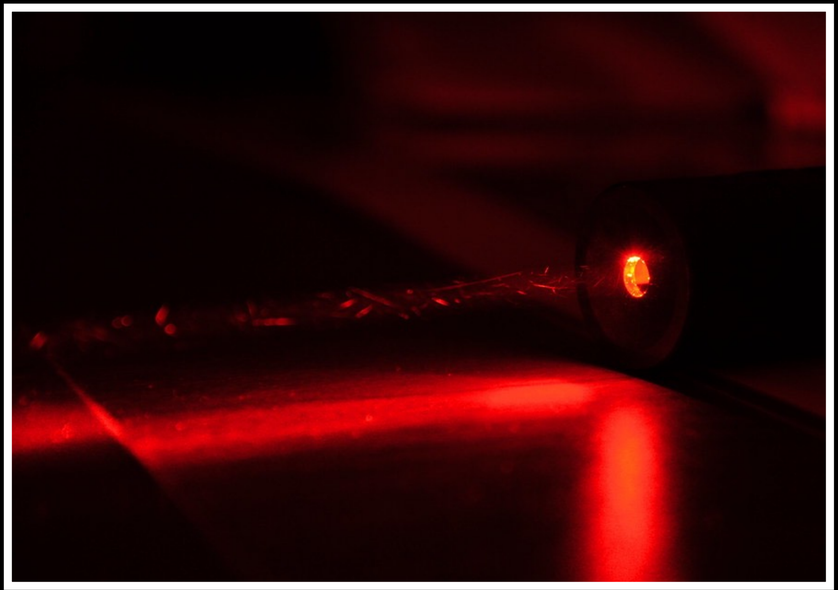
'coherent' regime

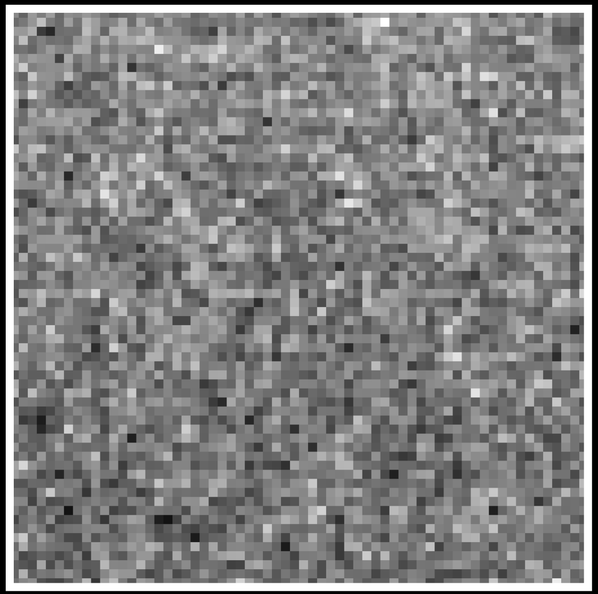


'incoherent' regime

optical speckle







'coherent' regime

'incoherent' regime

image formation

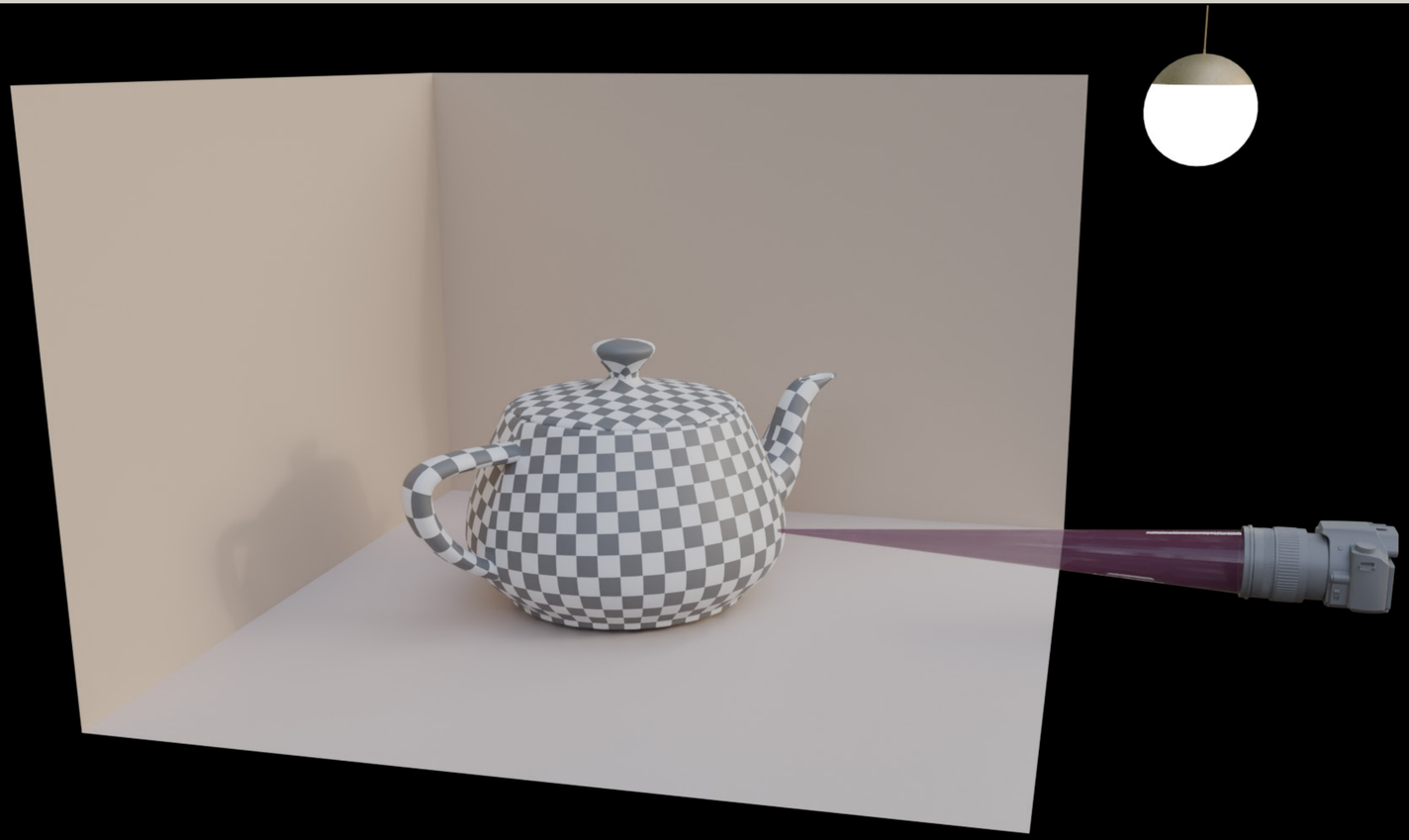


image formation

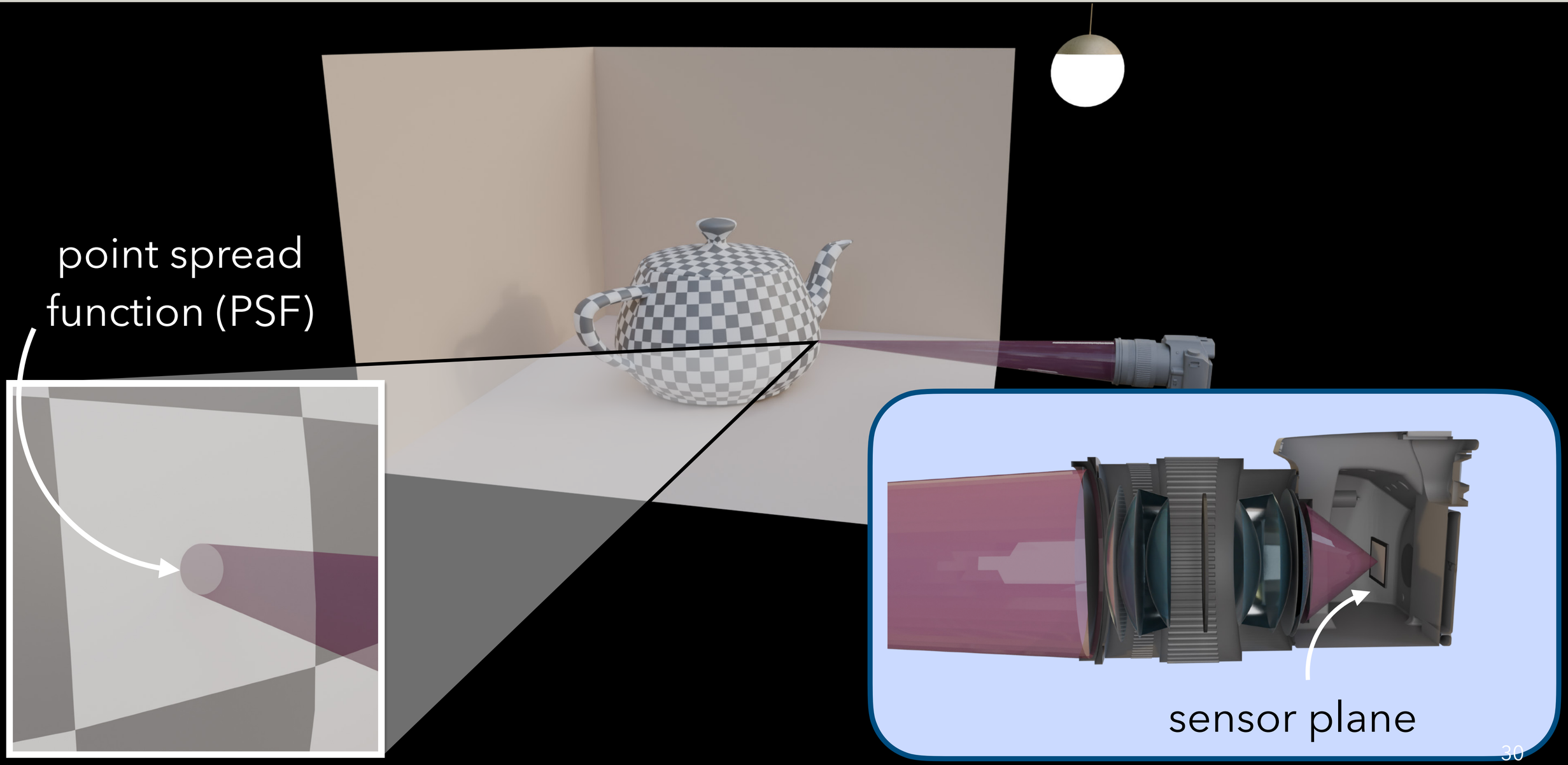
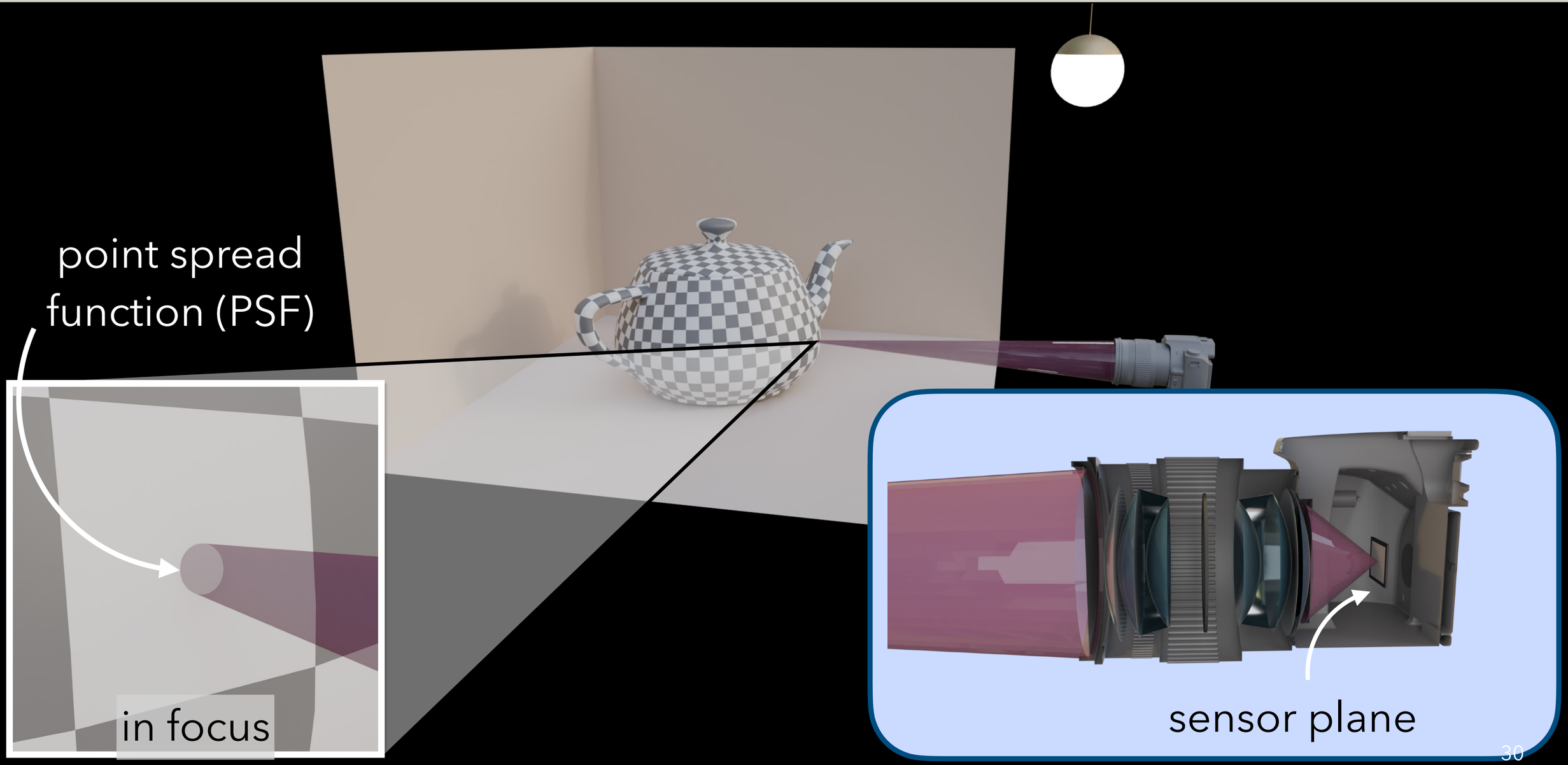
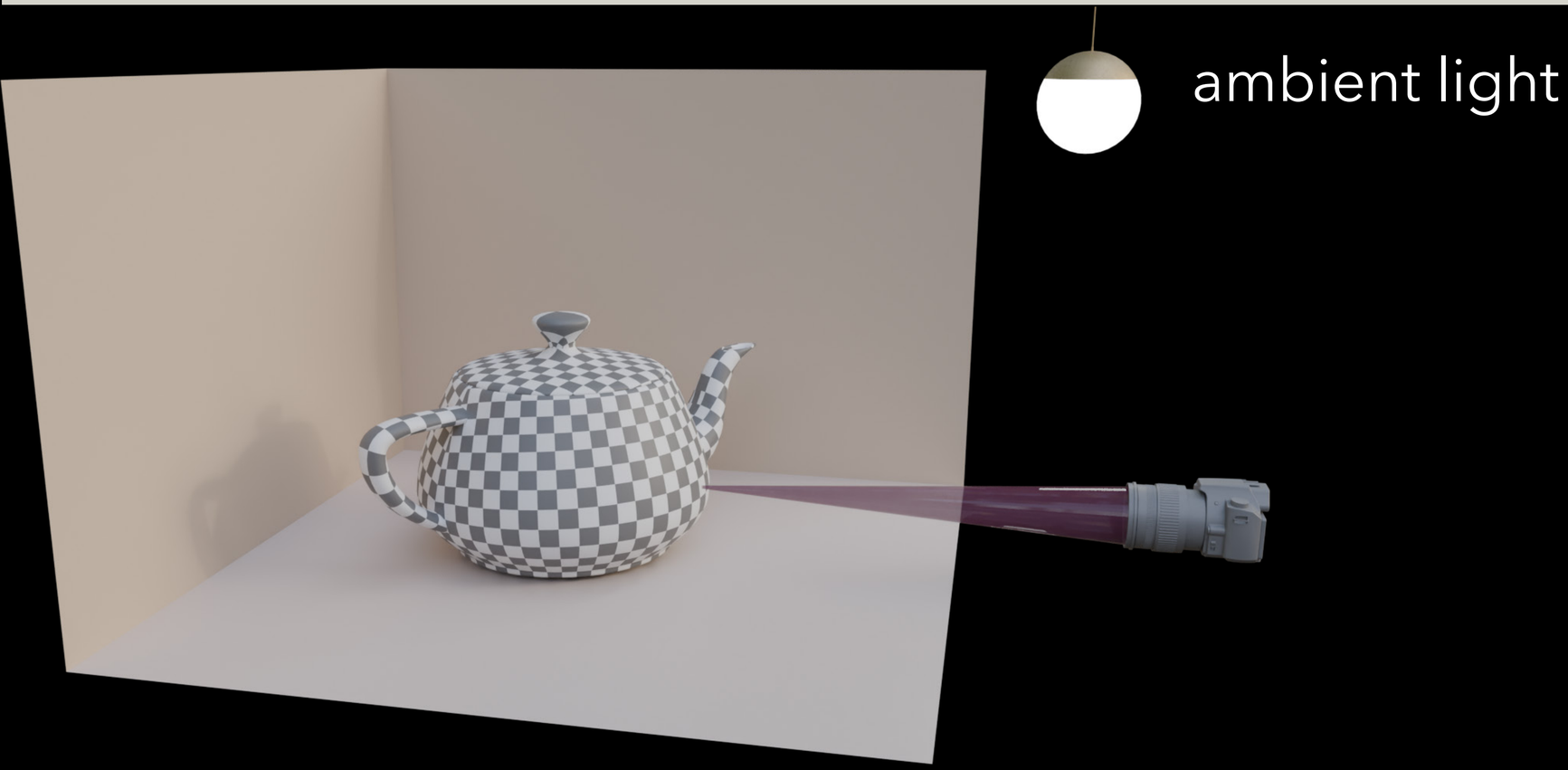


image formation

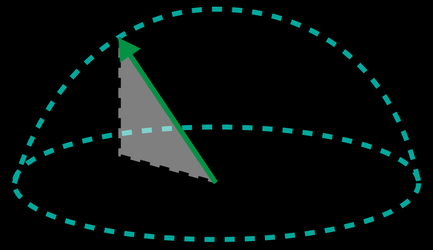


coherence area of illumination



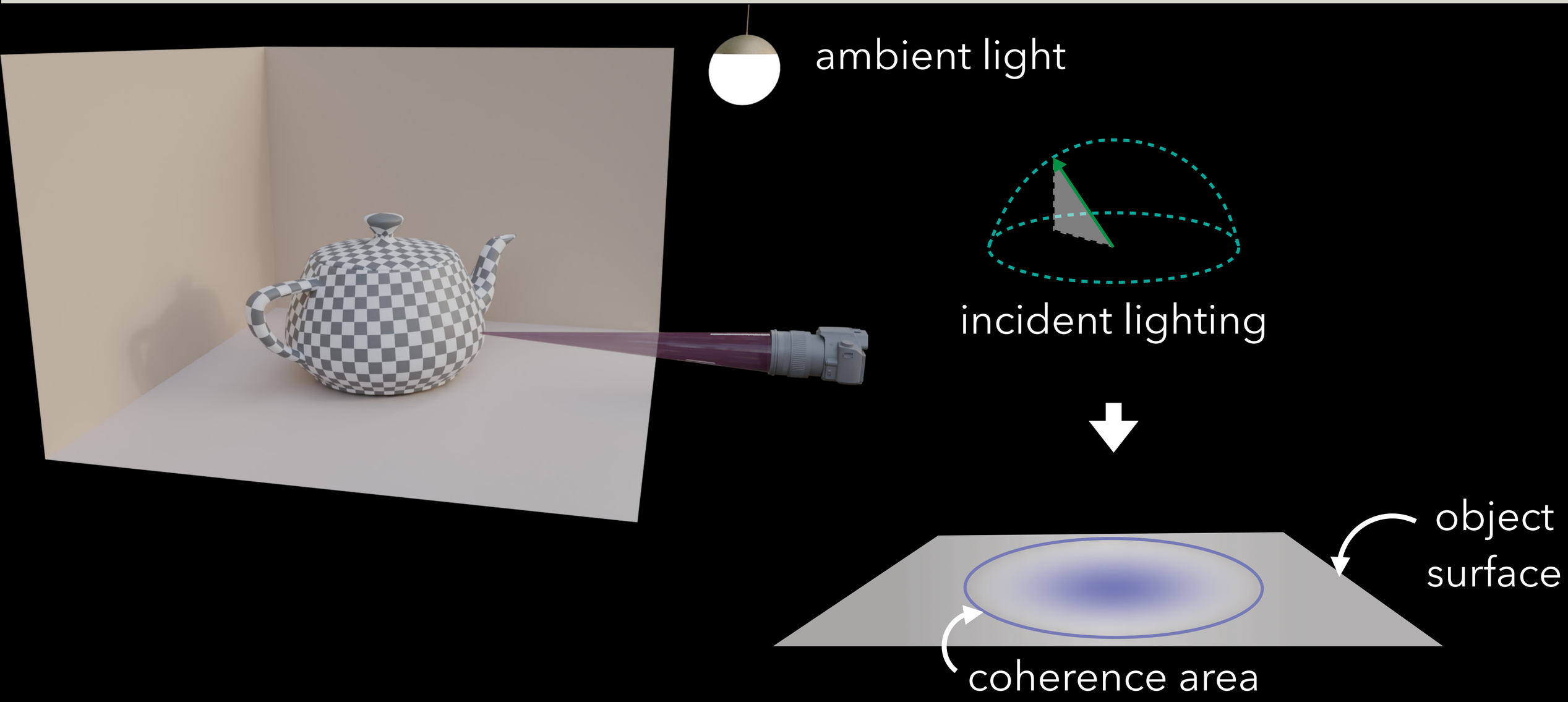
coherence area of illumination

ambient light

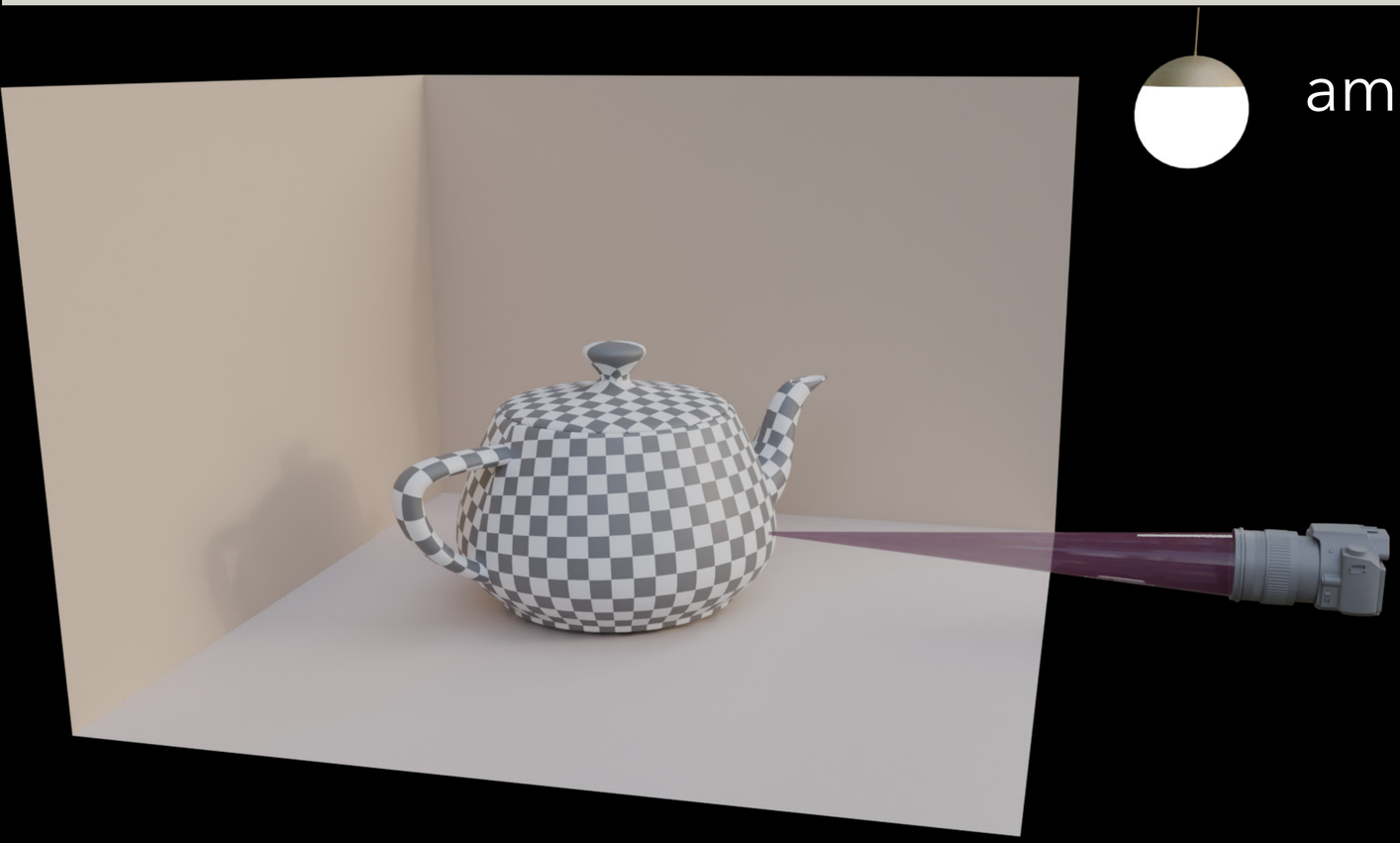


incident lighting

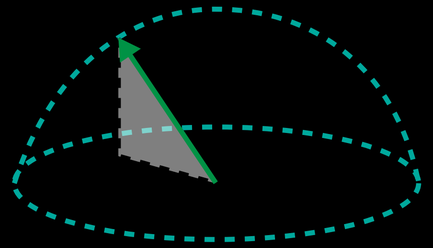
coherence area of illumination



coherence area of illumination



ambient light



incident lighting

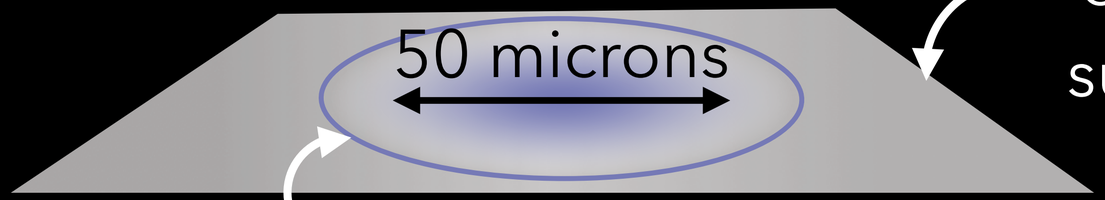
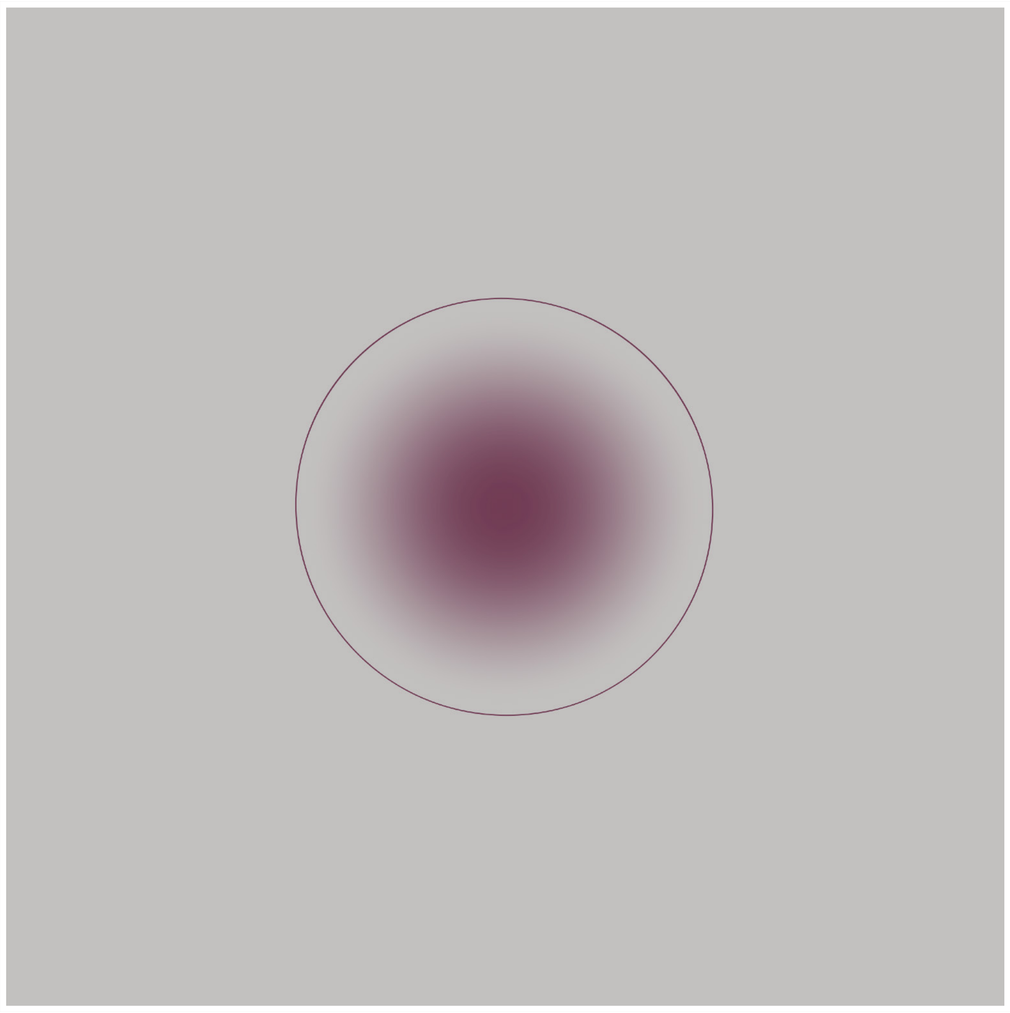


image formation: spatial summation



object surface

PSF

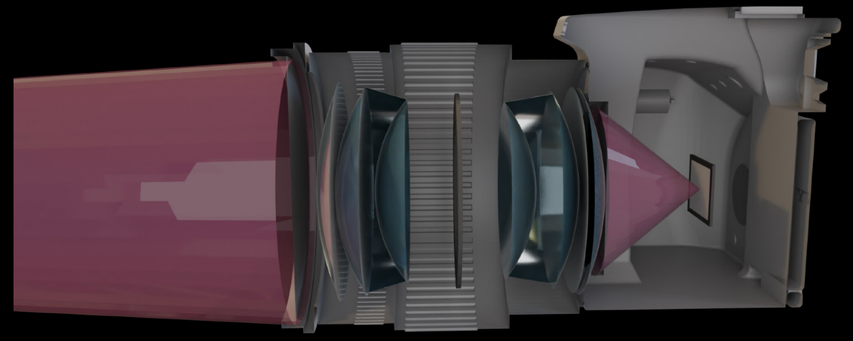
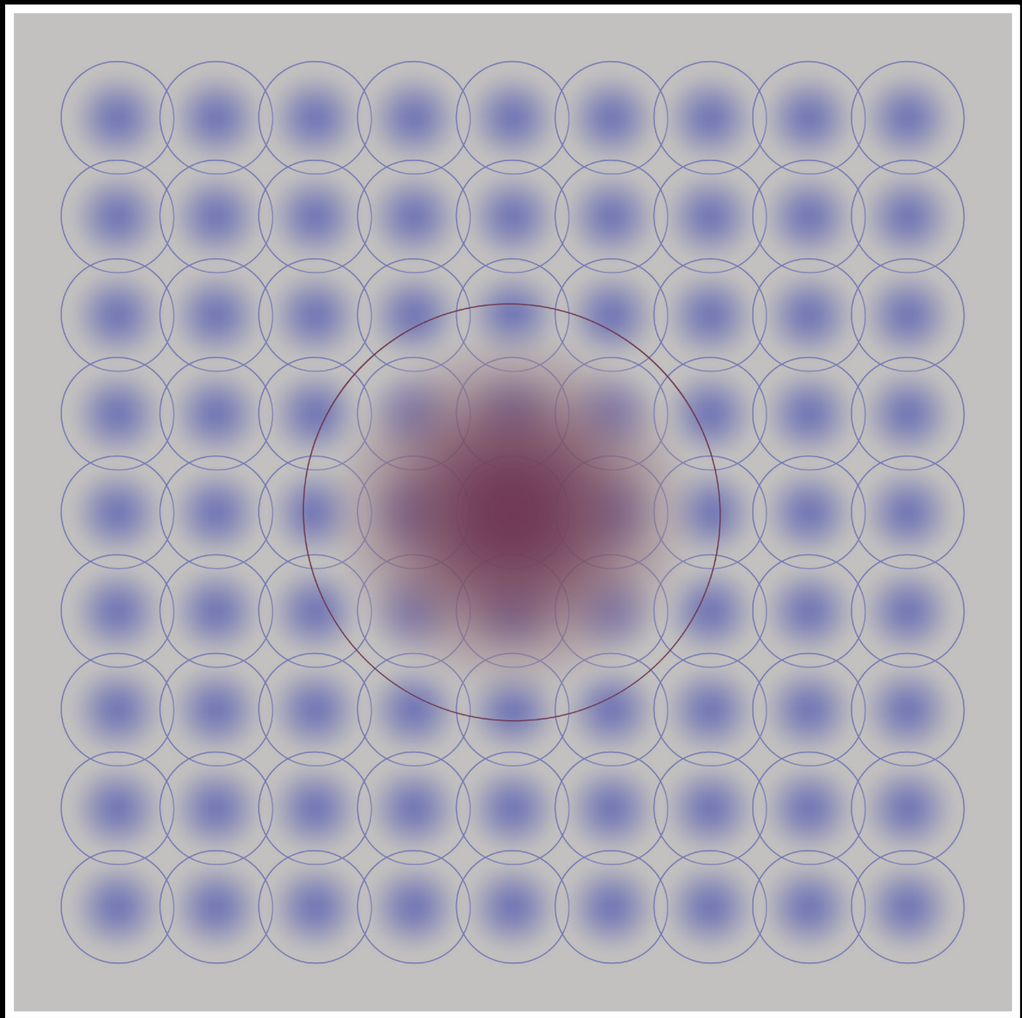


image formation: spatial summation



object surface

PSF

coherence area

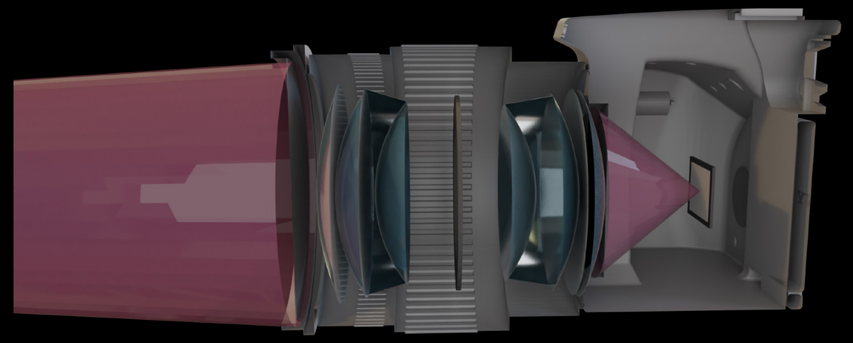
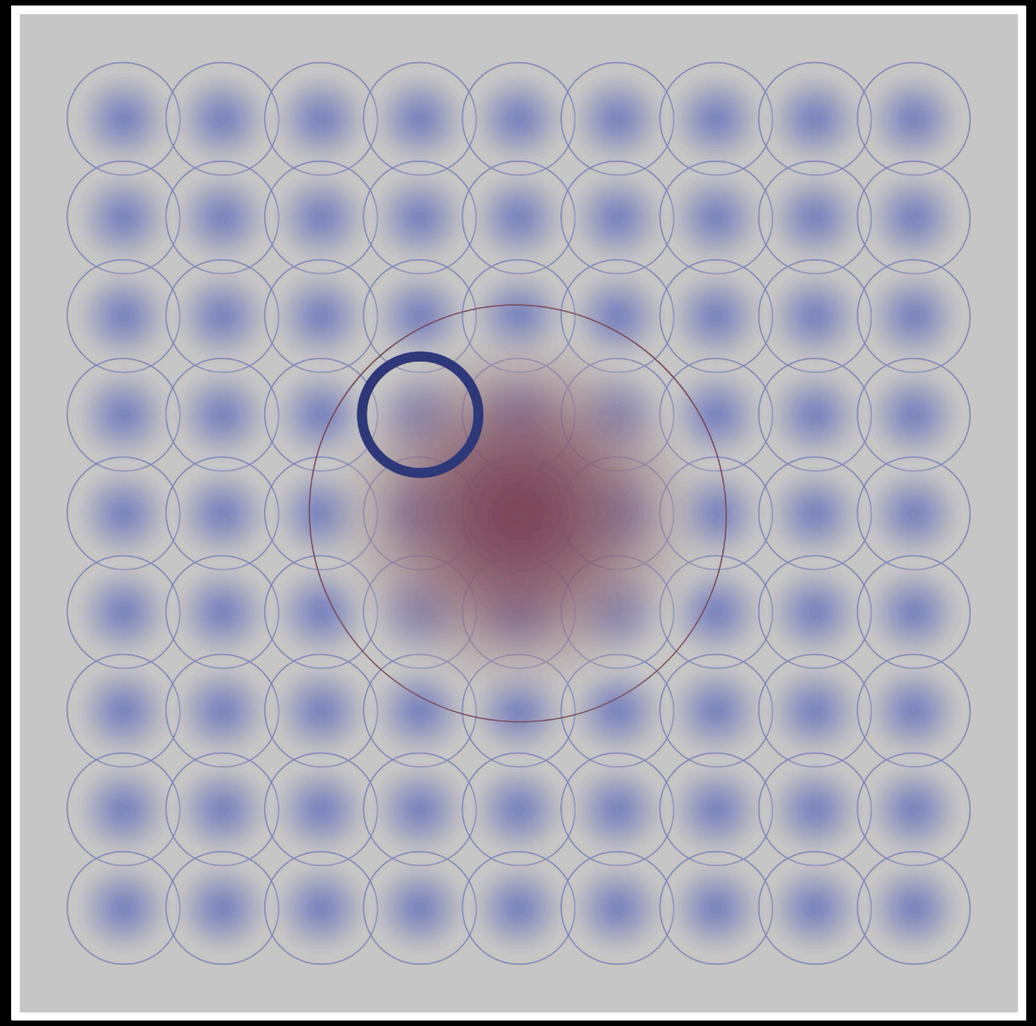
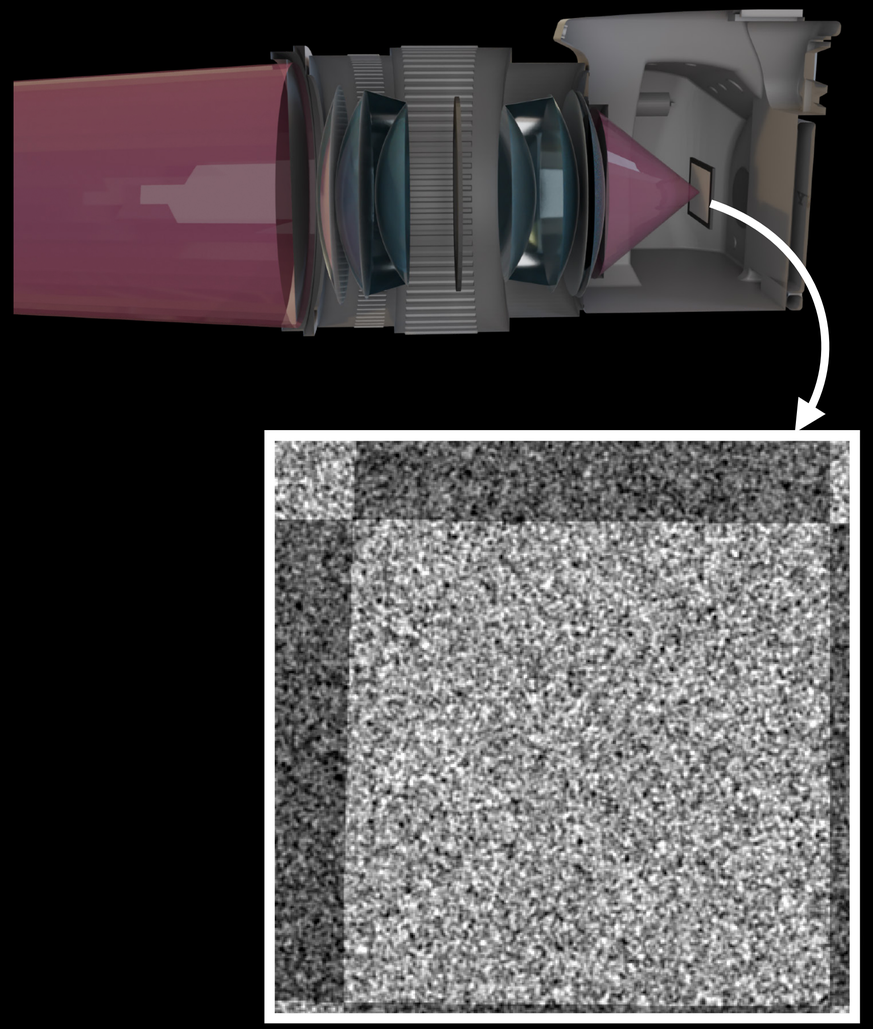


image formation: spatial summation



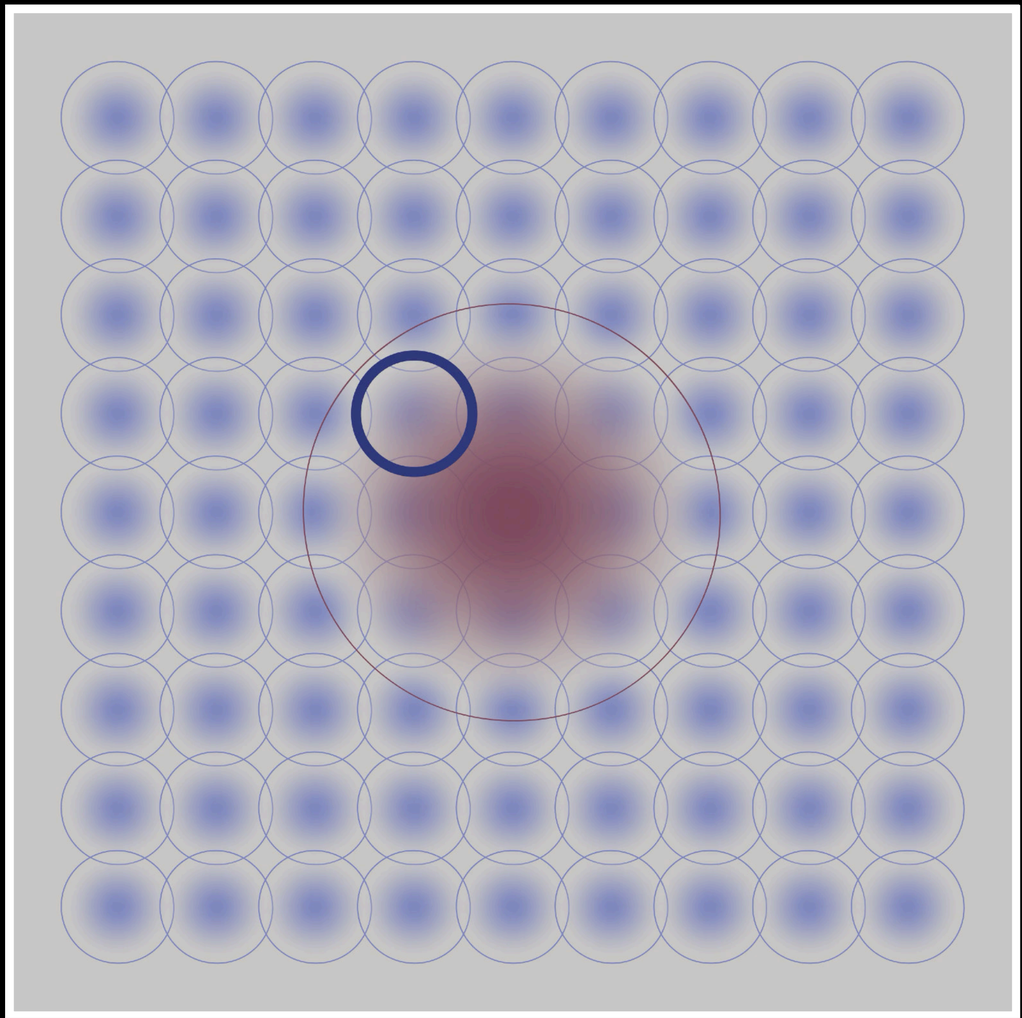
PSF

coherence area



object surface

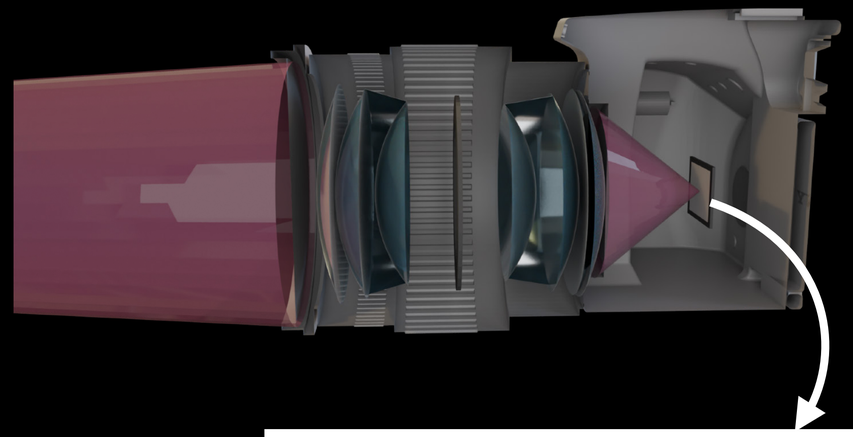
image formation: spatial summation

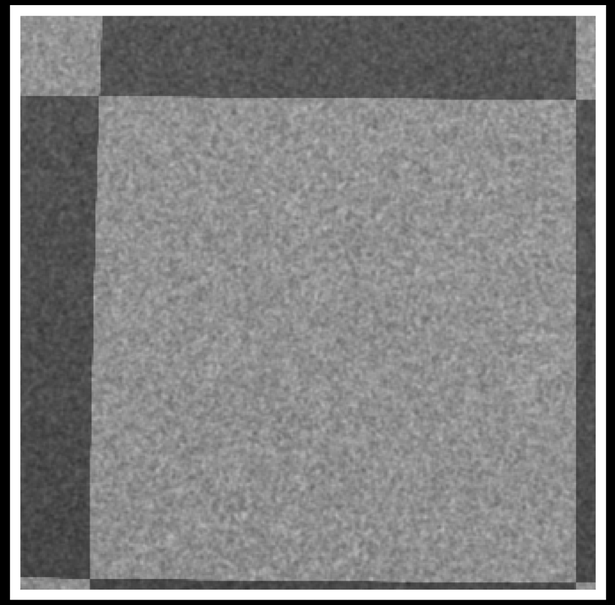


object surface

PSF

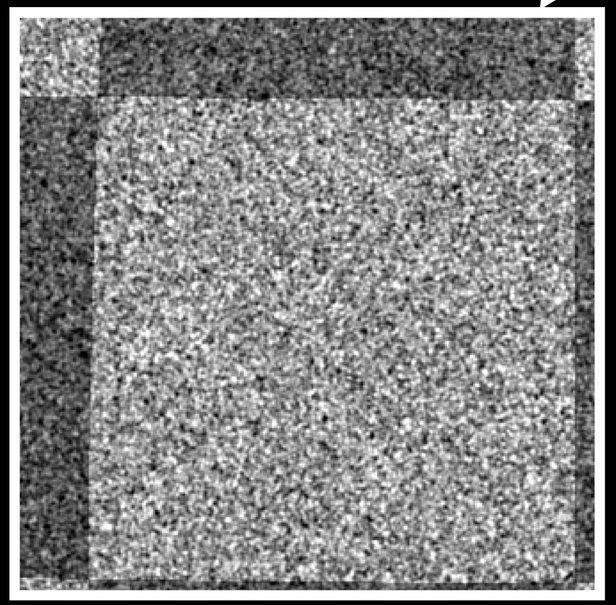
coherence area





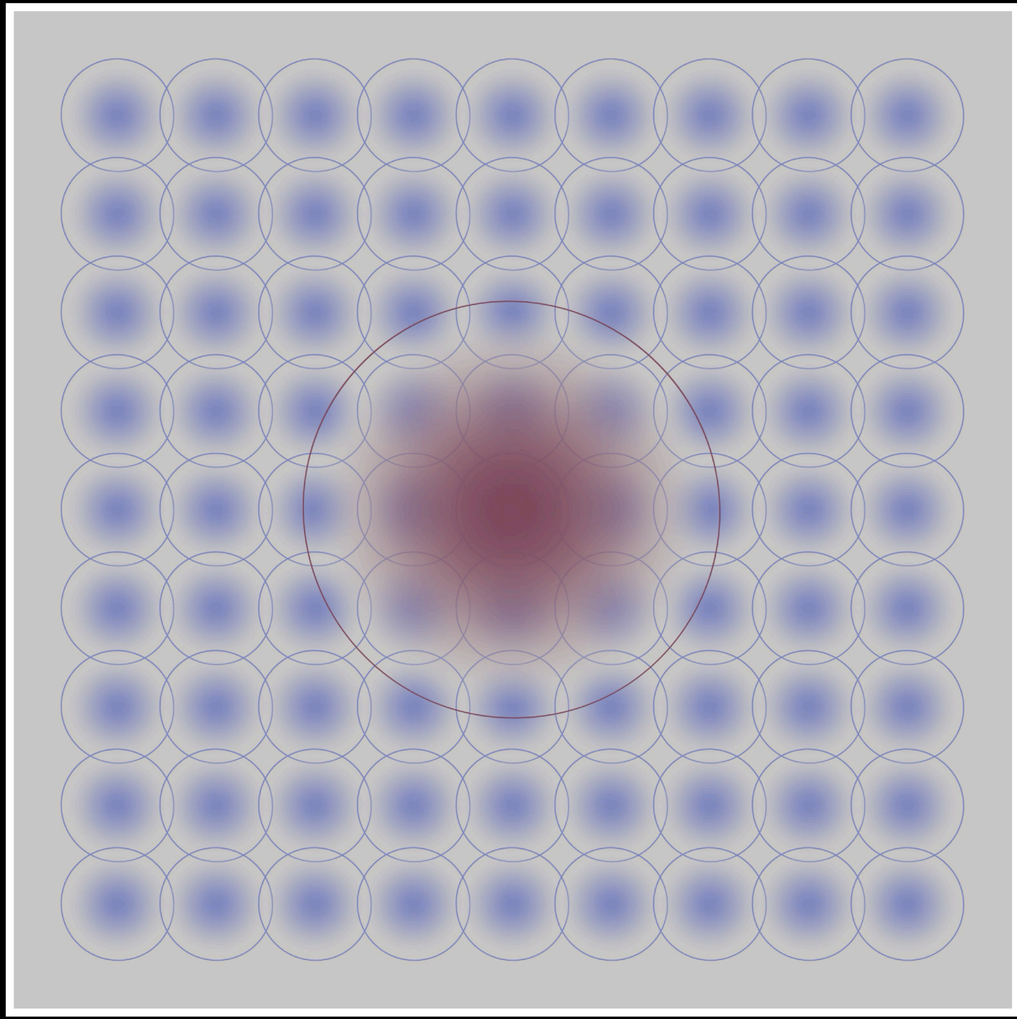
measured intensity

$= \Sigma$



speckle contributions

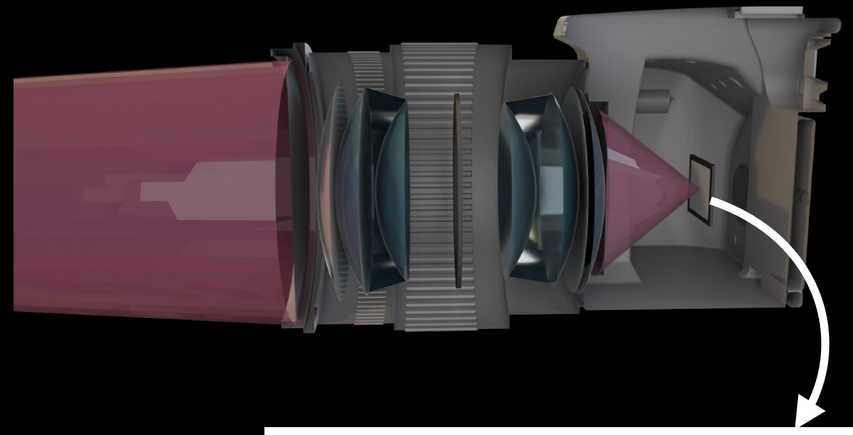
image formation: spatial summation

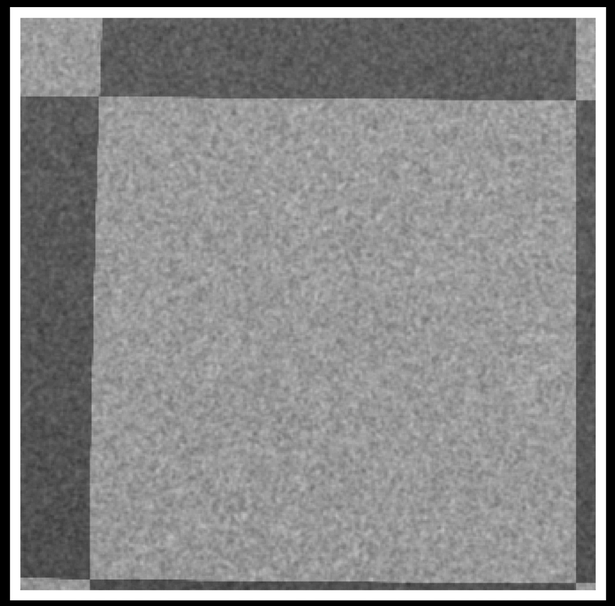


object surface

PSF

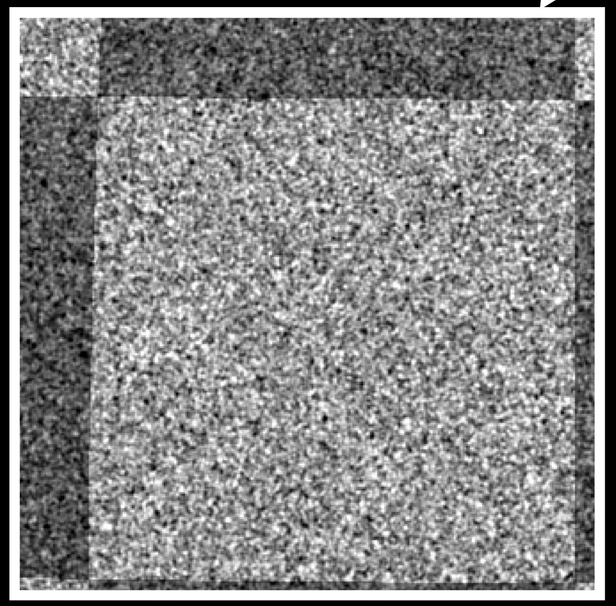
coherence area





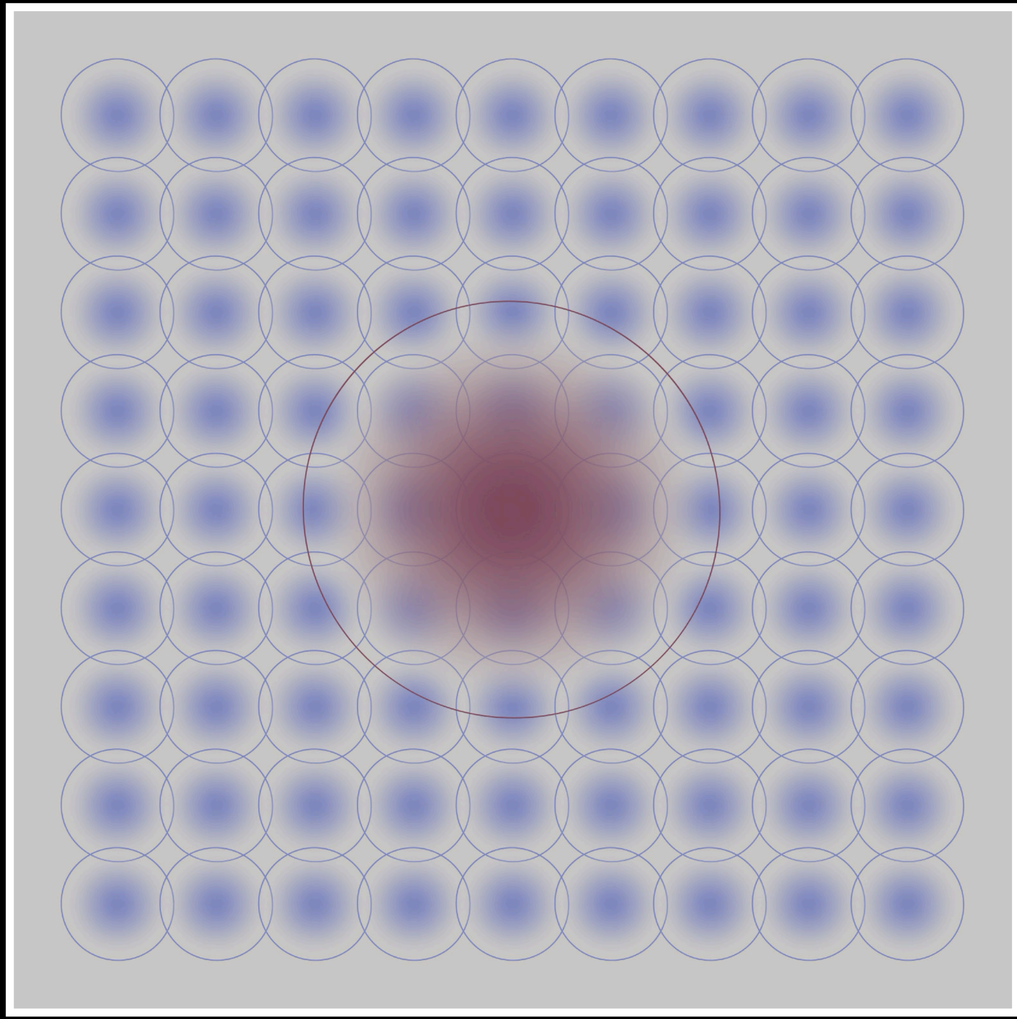
measured intensity

$=\Sigma$



speckle contributions

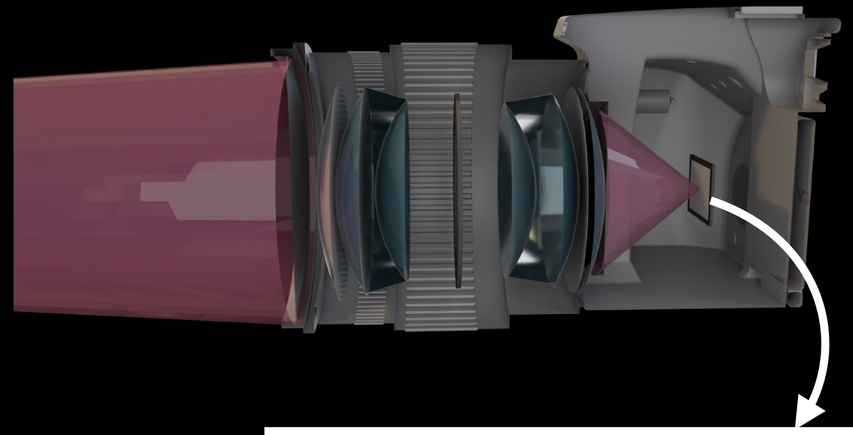
image formation: spatial summation

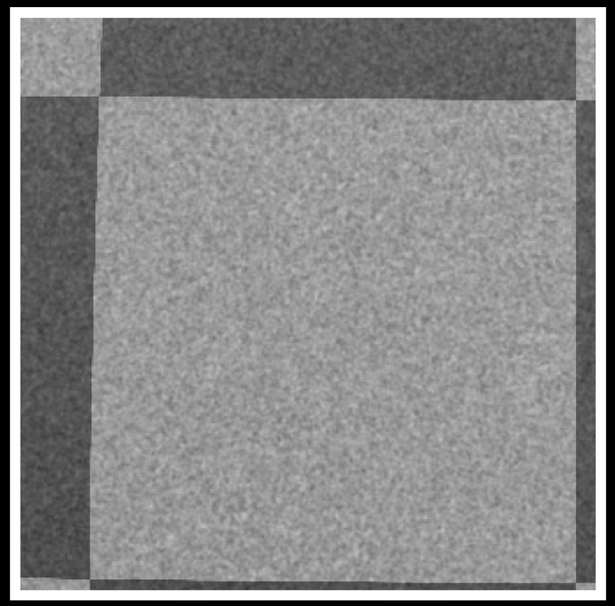


object surface

PSF

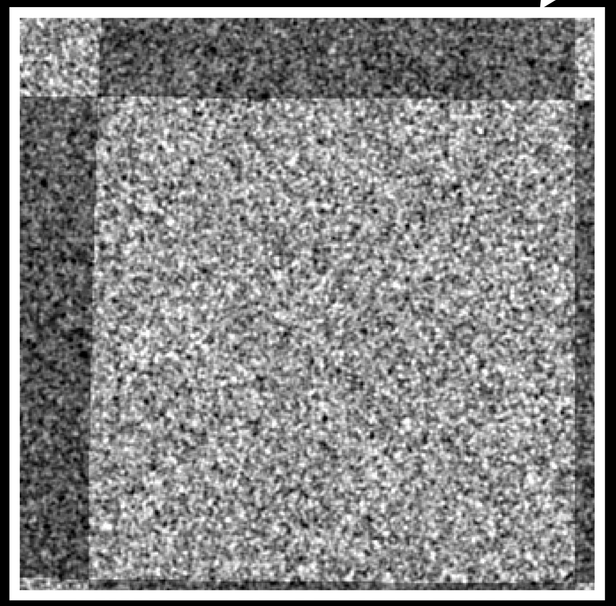
coherence area





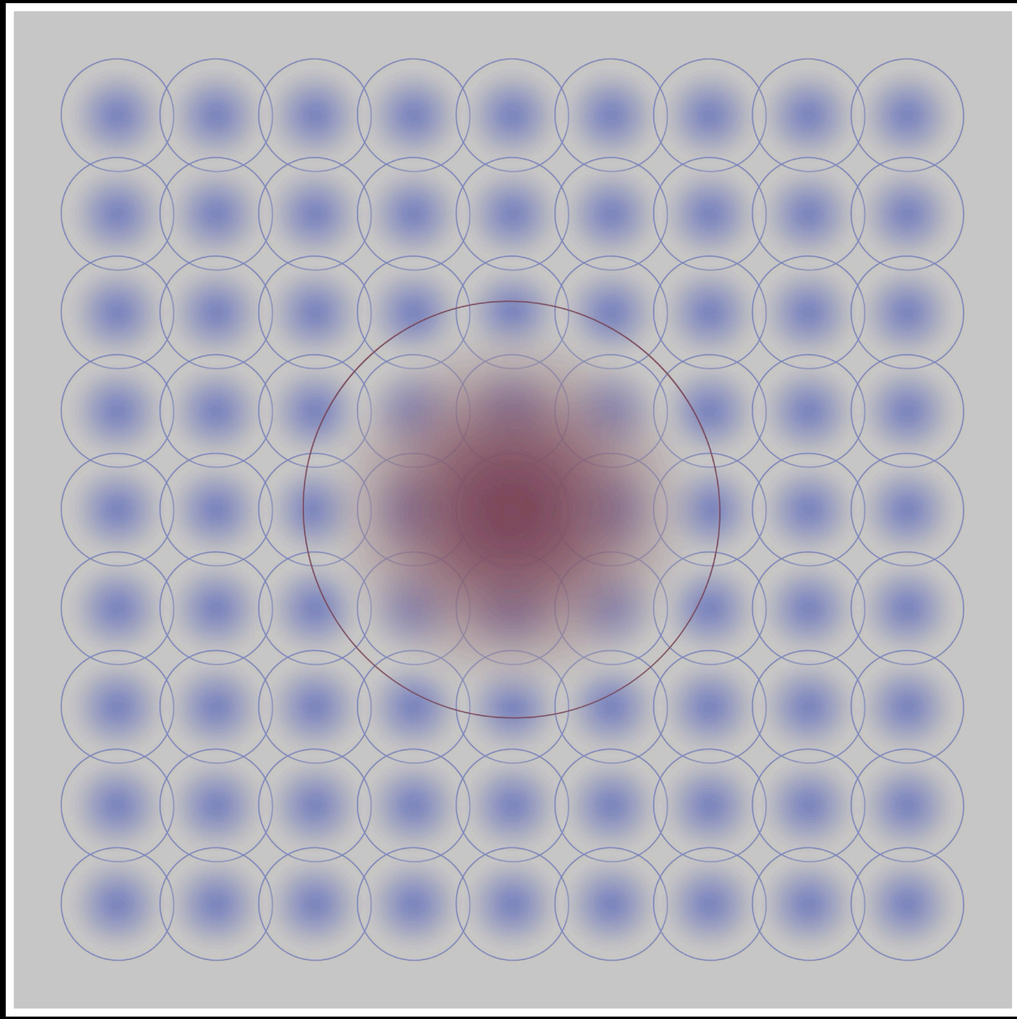
measured intensity

$=\Sigma$



speckle contributions

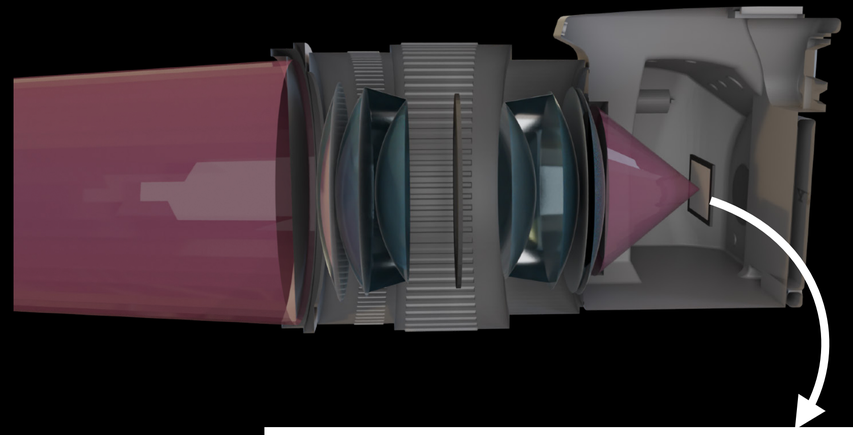
image formation: spatial summation

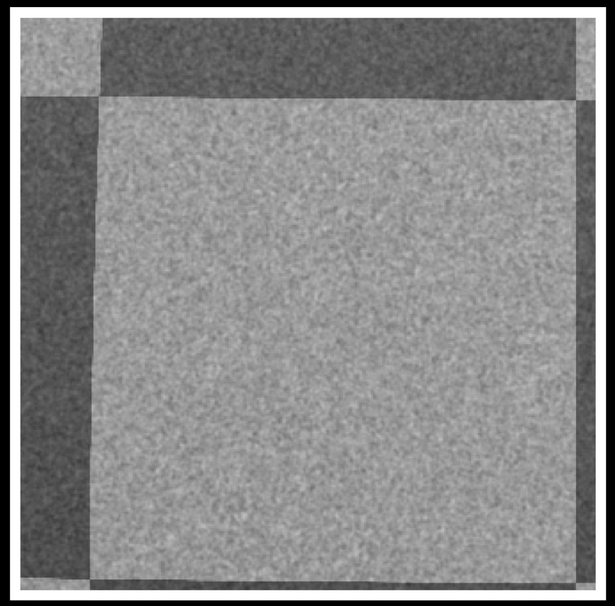


object surface

PSF

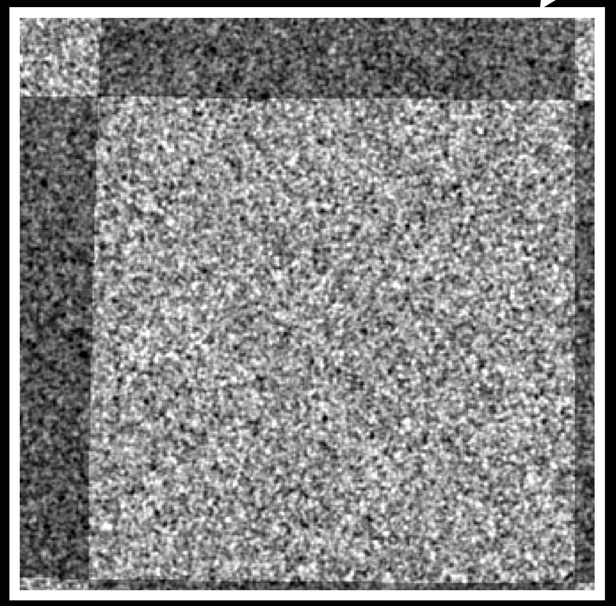
coherence area





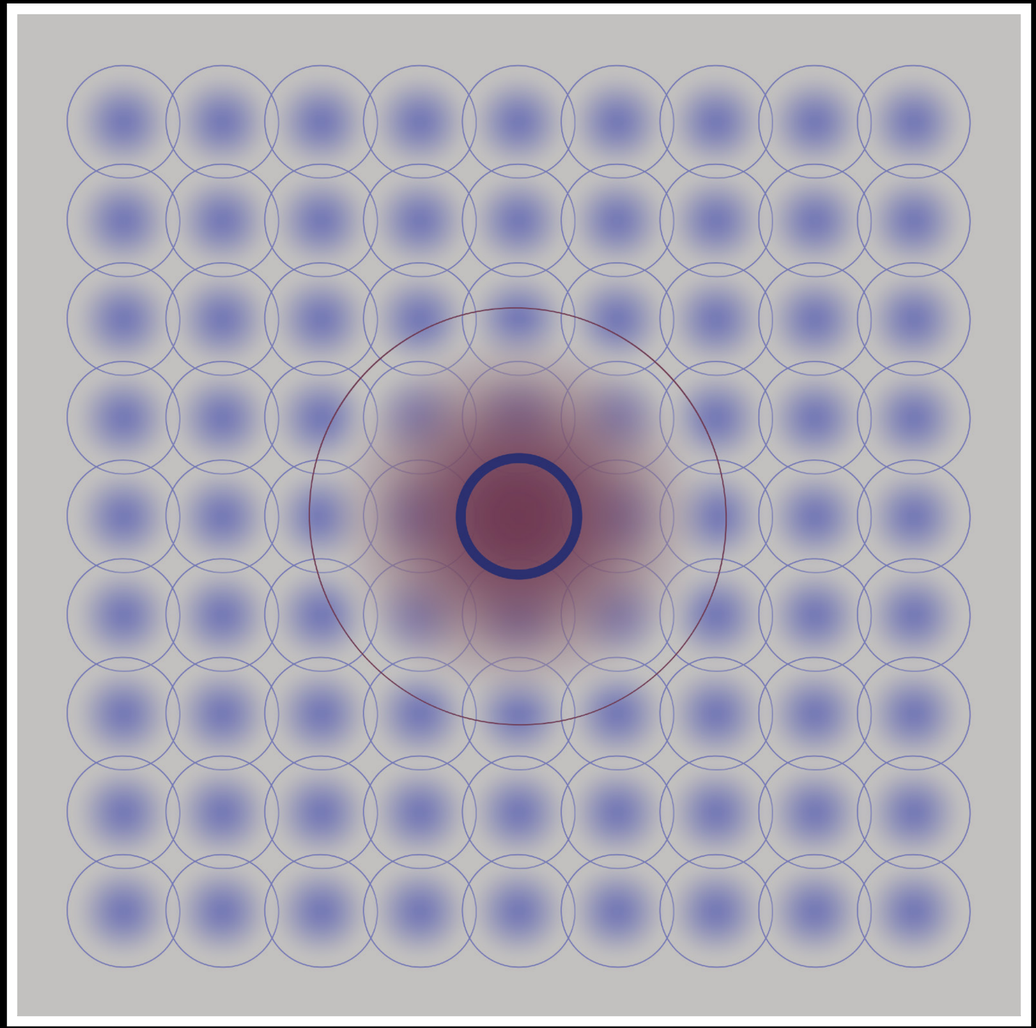
measured intensity

$=\Sigma$



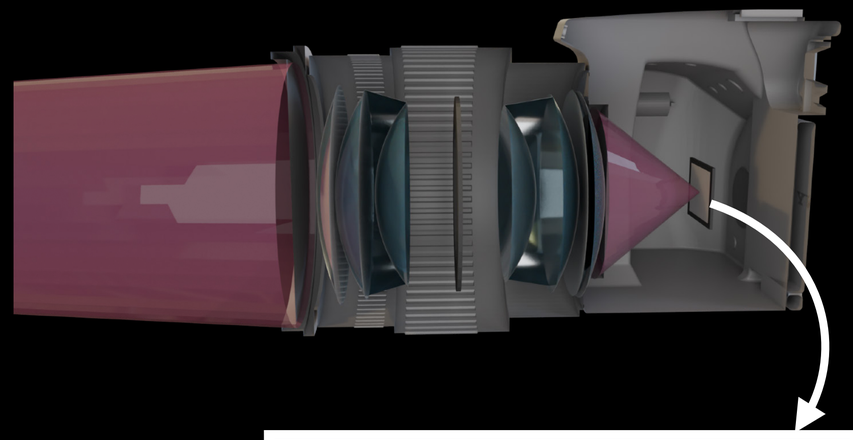
speckle contributions

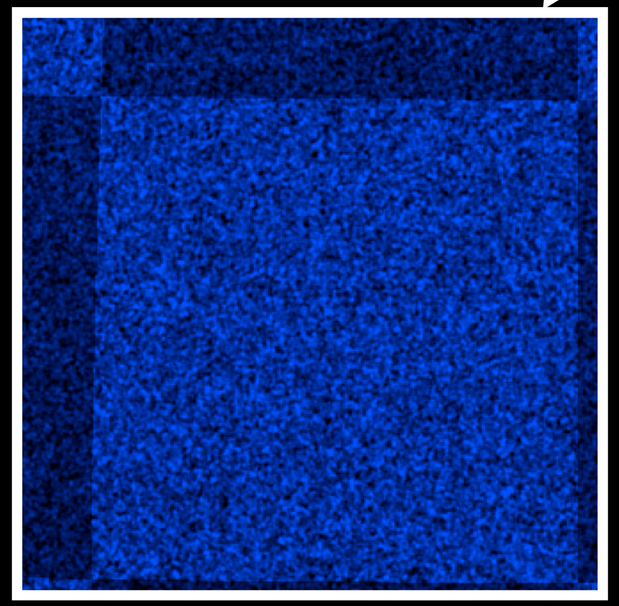
image formation: spectral summation



PSF

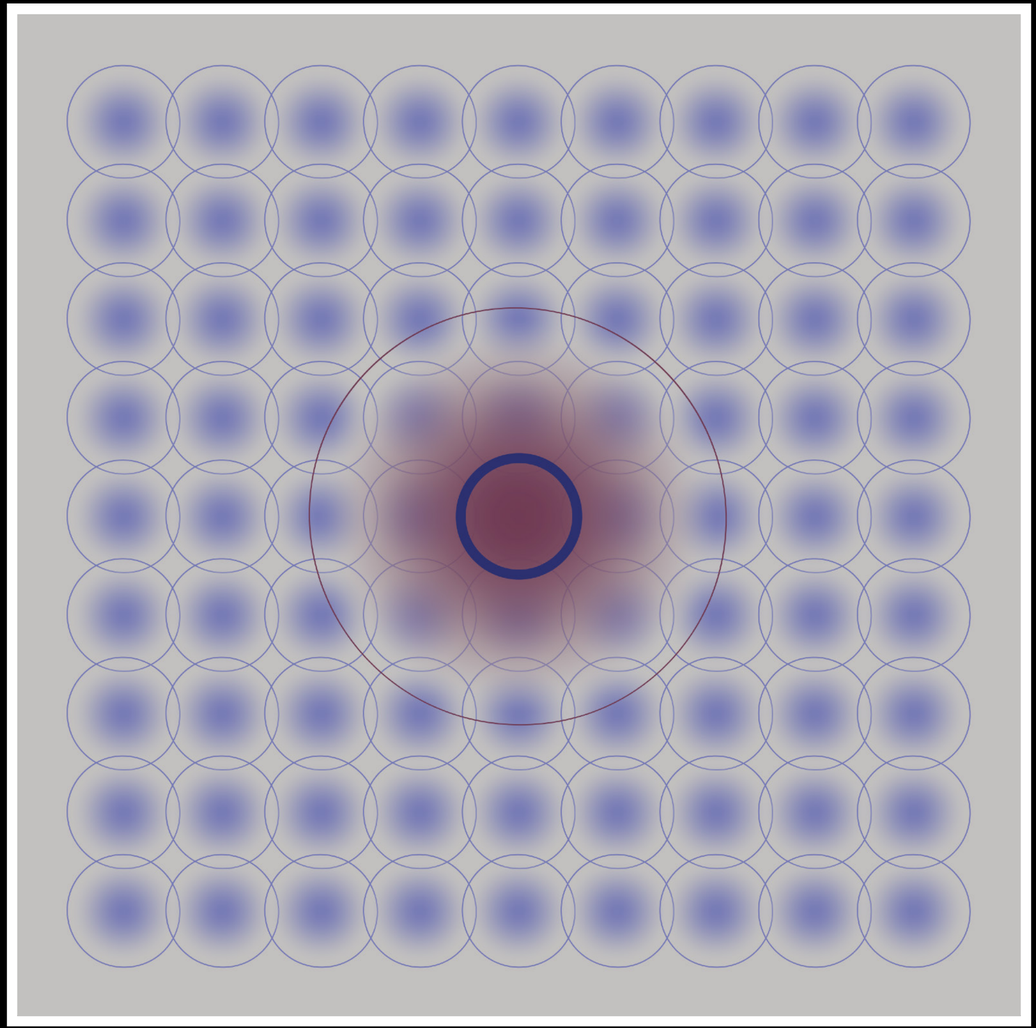
coherence area





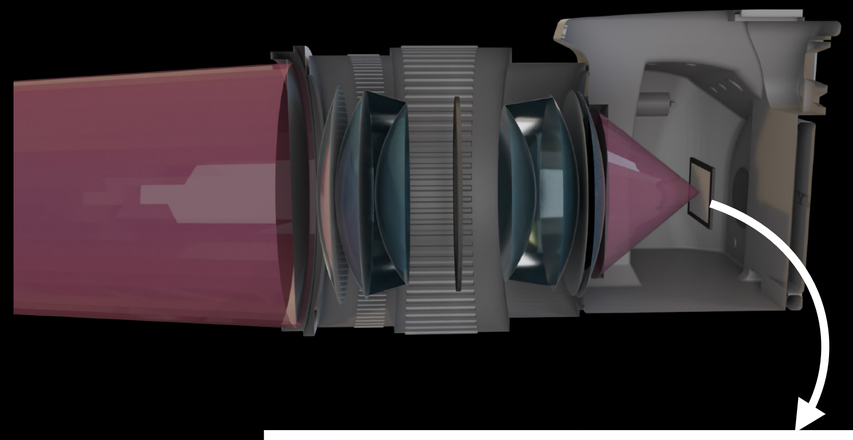
spectral contributions

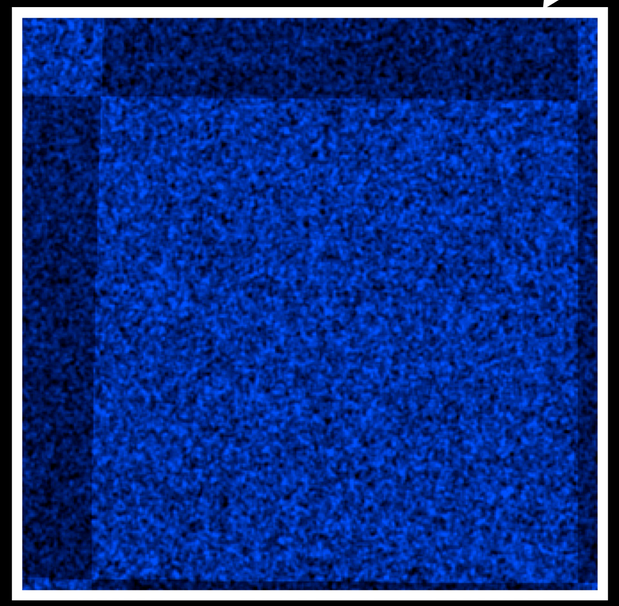
image formation: spectral summation



PSF

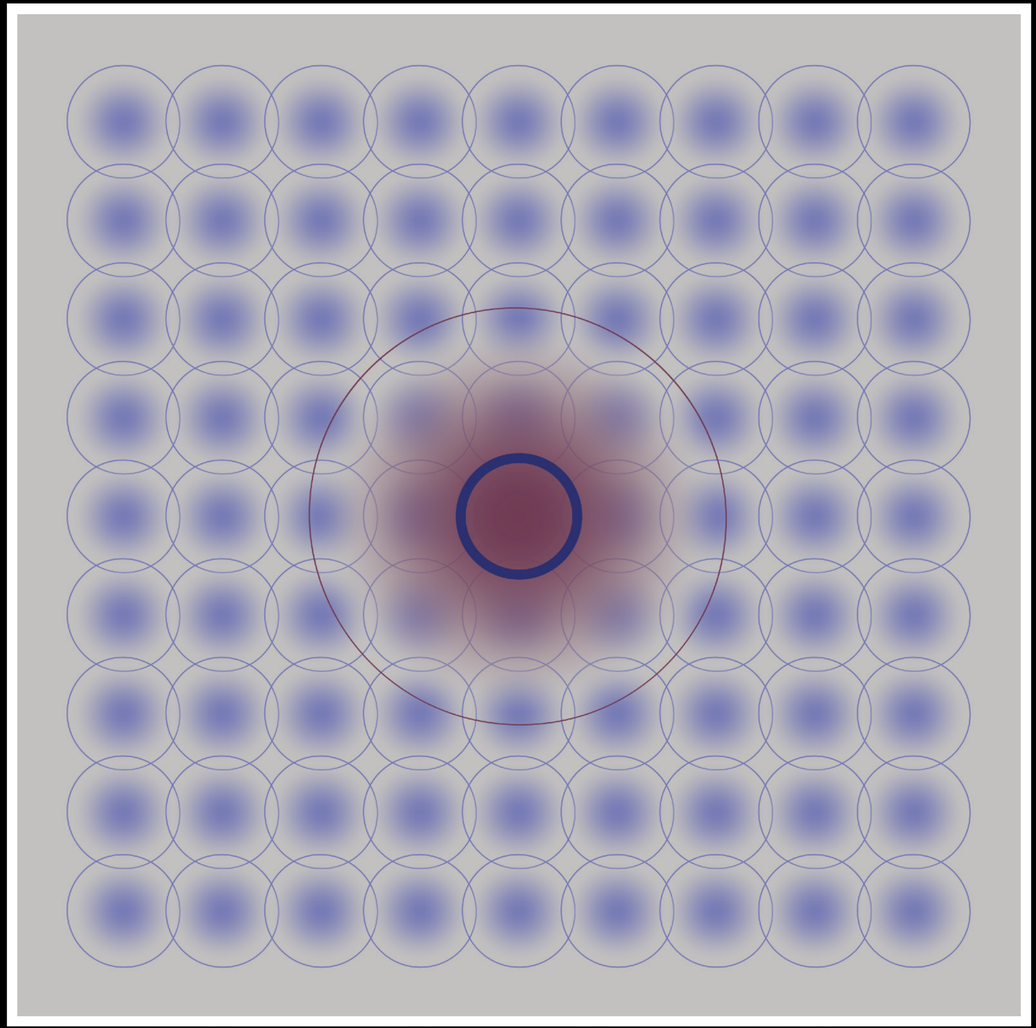
coherence area





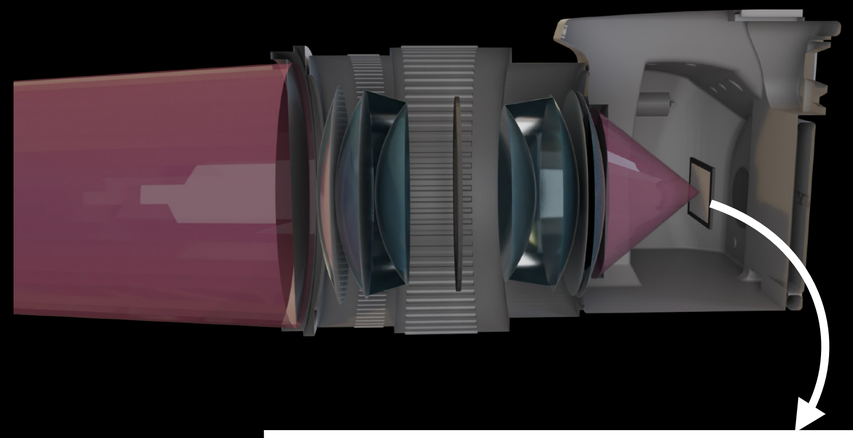
spectral contributions

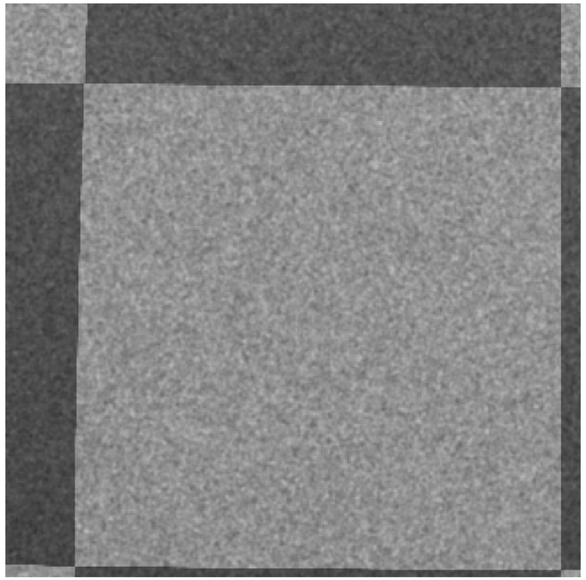
image formation: spectral summation



PSF

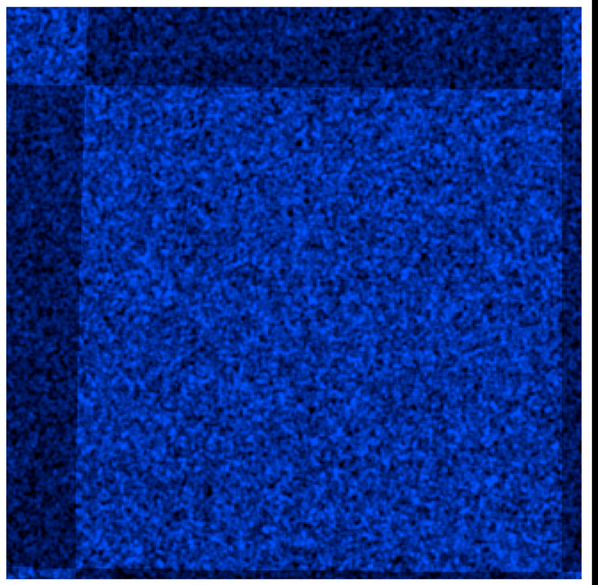
coherence area





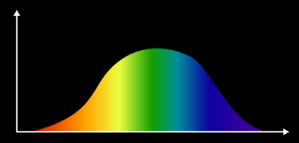
measured intensity

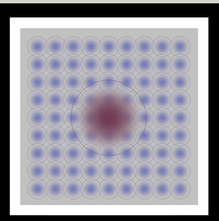
$= \sum$



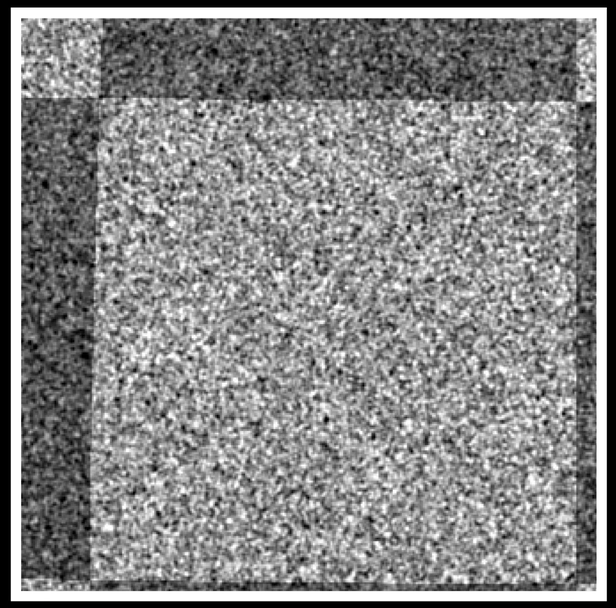
spectral contributions

strength of speckle



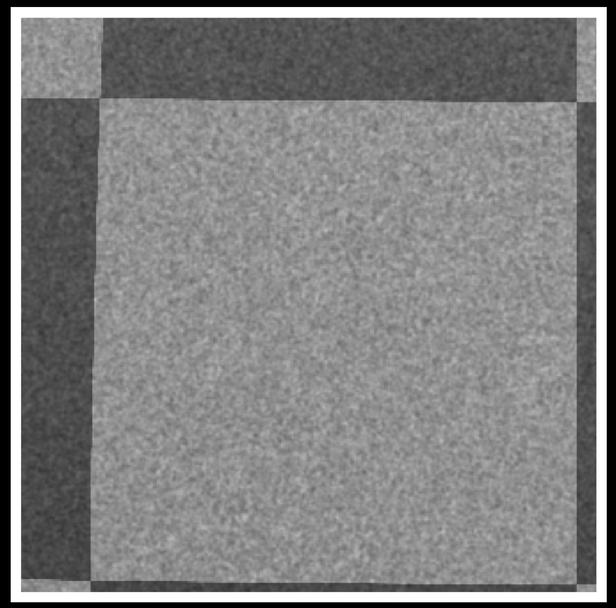


$$\sum\sum$$



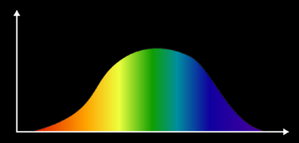
speckle contributions

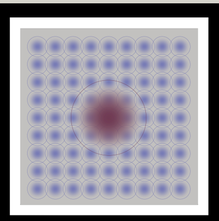
$$=$$



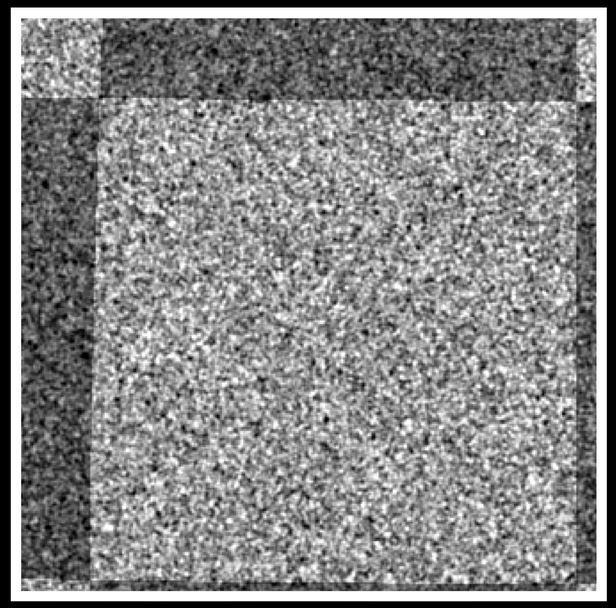
measured intensity

strength of speckle



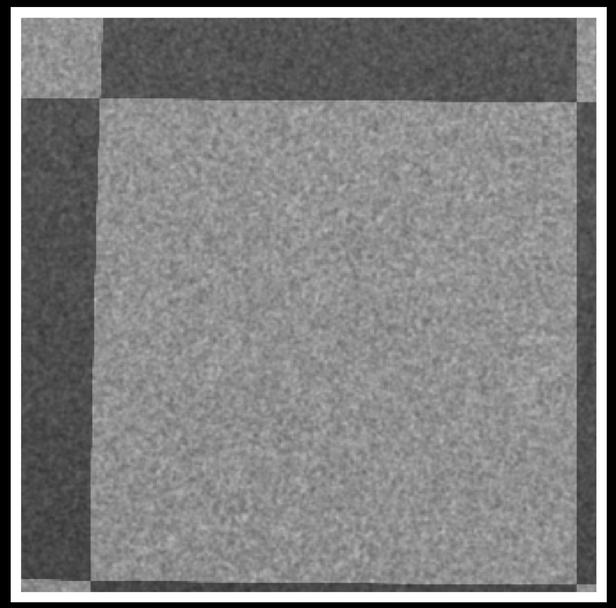


$$\sum\sum$$



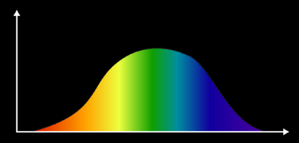
speckle contributions

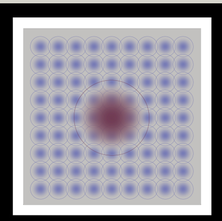
$$=$$



measured intensity

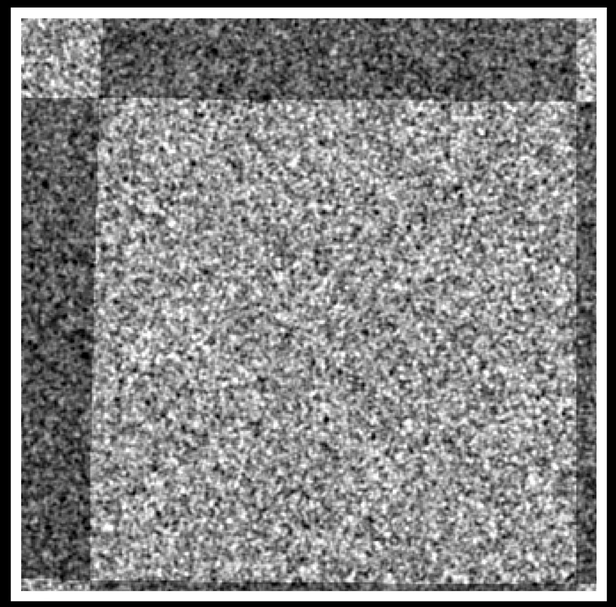
strength of speckle





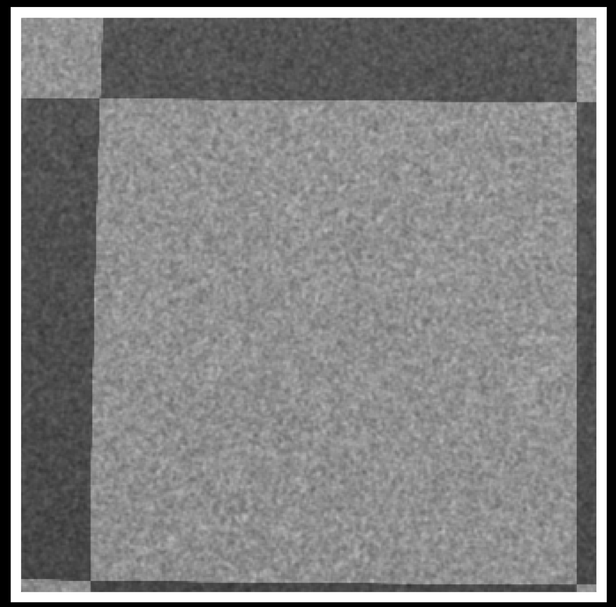
$$\sum \sum_{\mathcal{Q}}$$

spatial



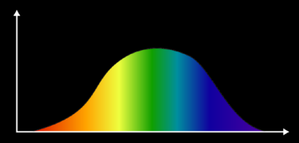
speckle contributions

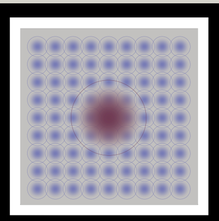
=



measured intensity

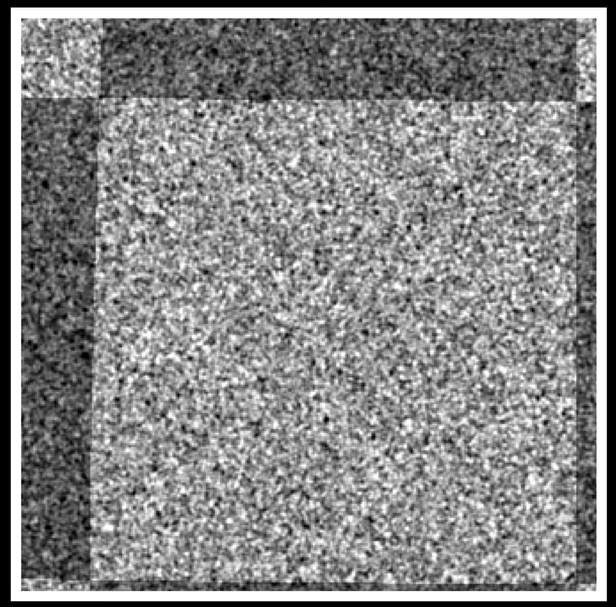
strength of speckle





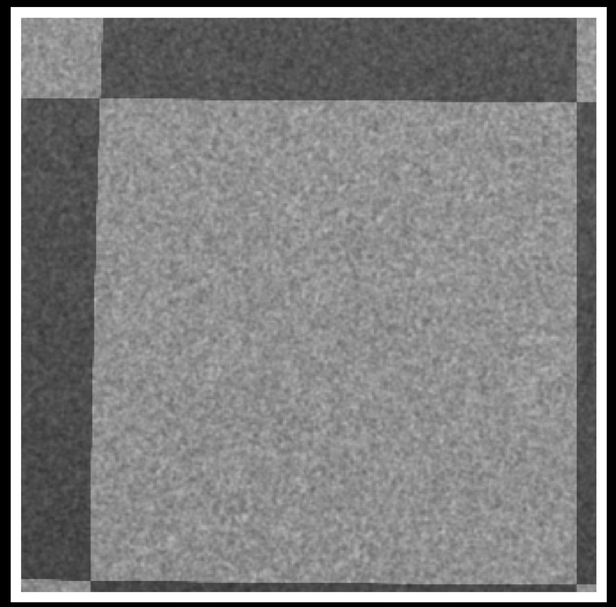
$$\sum_{M} \sum_{Q}$$

spectral spatial



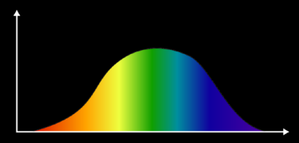
speckle contributions

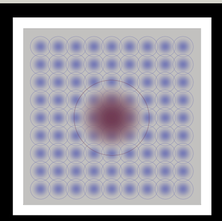
$=$



measured intensity

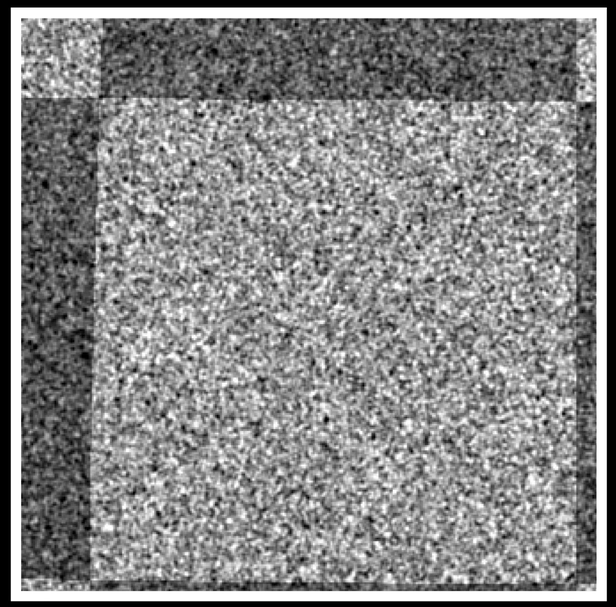
strength of speckle





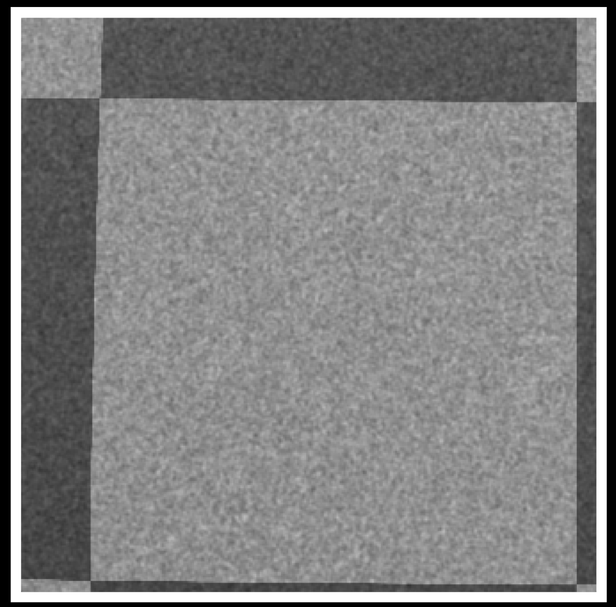
$$\sum_{M}\sum_{Q}$$

spectral spatial



speckle contributions

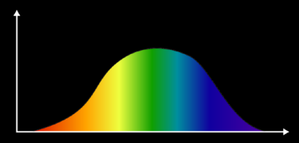
$=$

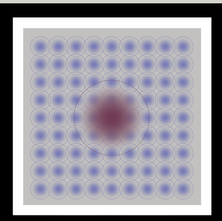


measured intensity

$$\text{speckle strength} = \frac{1}{M\,Q}$$

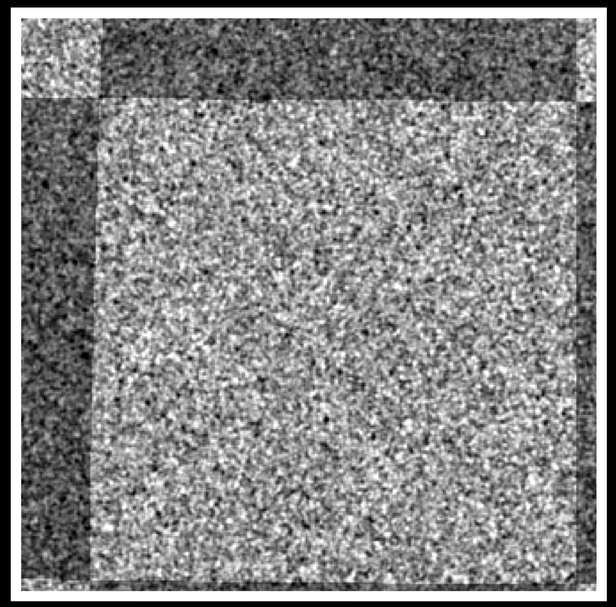
strength of speckle





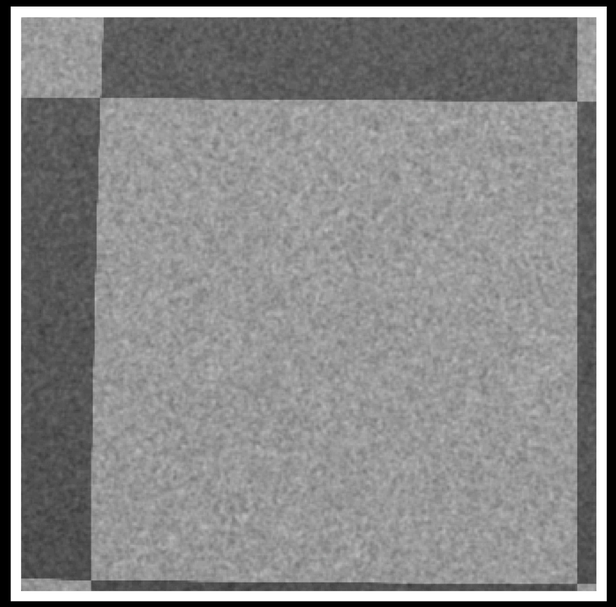
$$\sum_{M}\sum_{Q}$$

spectral spatial



speckle contributions

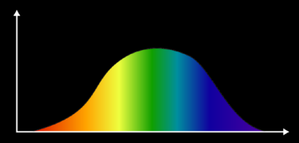
$=$

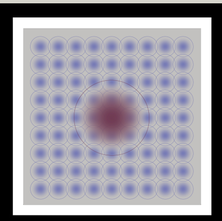


measured intensity

$$\text{speckle strength} = \frac{1}{M\,Q}$$

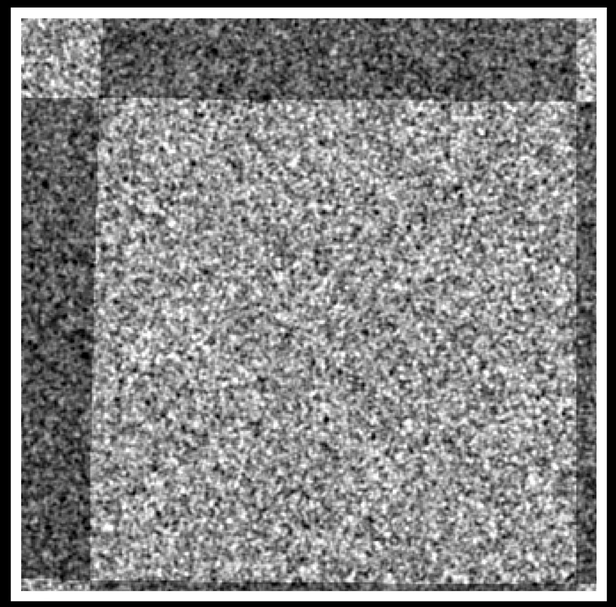
strength of speckle





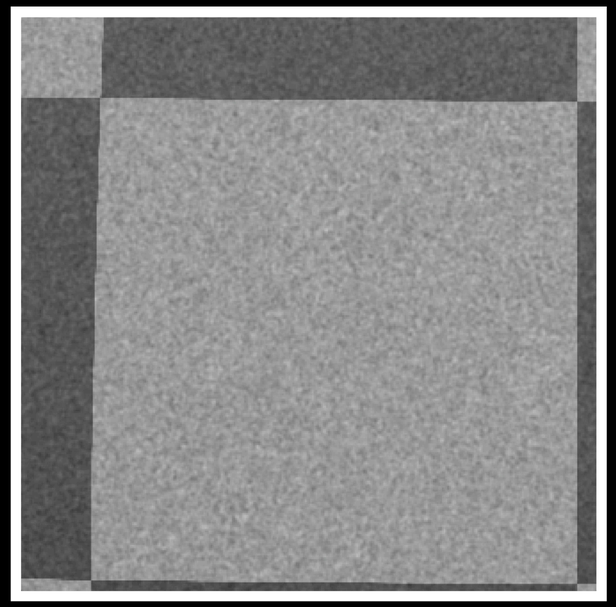
$$\sum_{M}\sum_{Q}$$

spectral spatial



speckle contributions

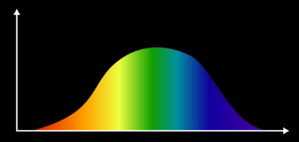
$=$

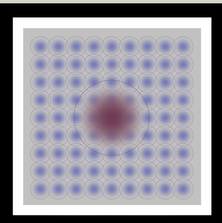


measured intensity

$$\text{speckle strength} = \frac{1}{M\,Q}$$

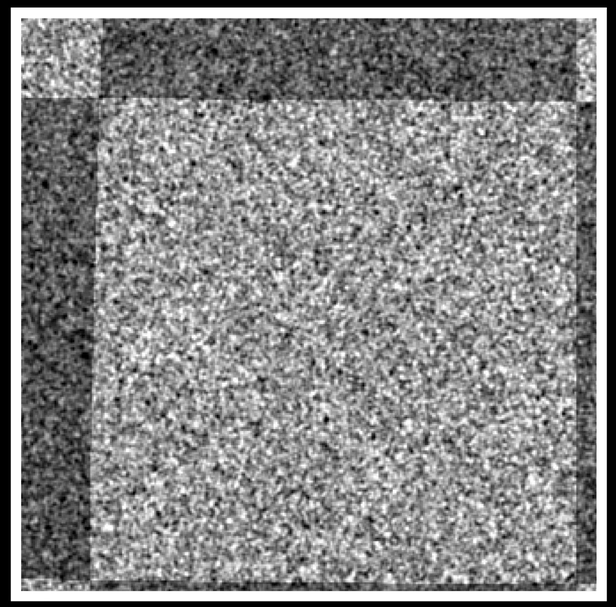
strength of speckle





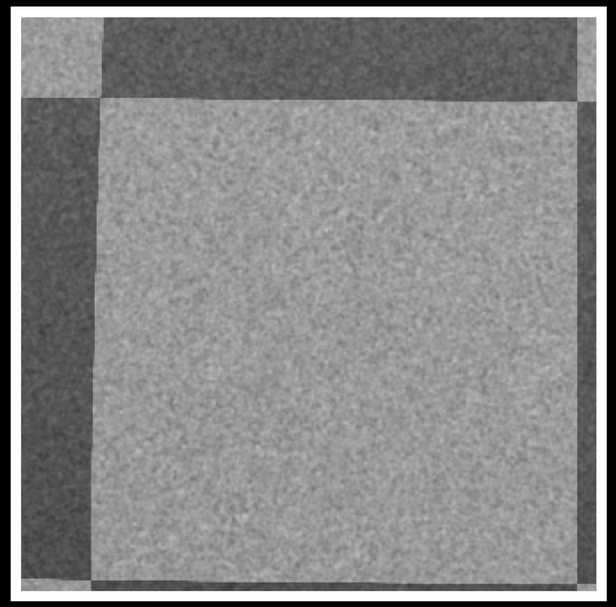
$$\sum_{M} \sum_{Q}$$

spectral spatial



speckle contributions

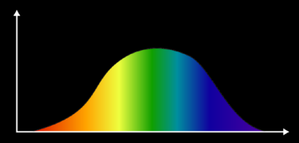
$=$

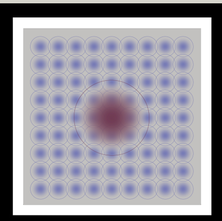


weakened speckle

$$\text{speckle strength} = \frac{1}{M\,Q}$$

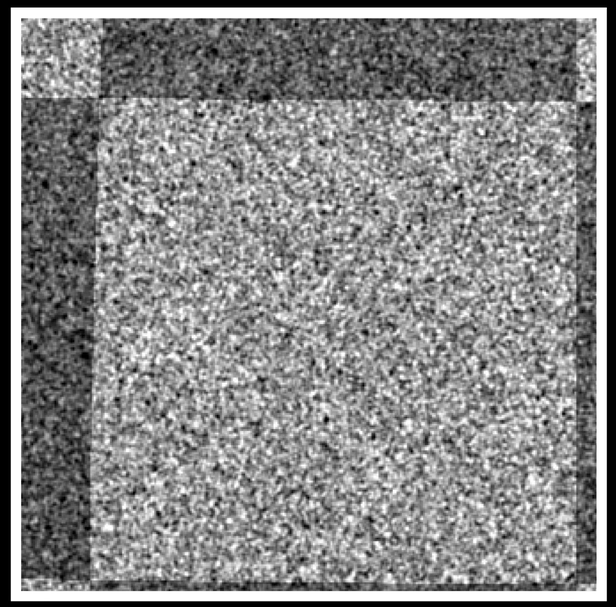
'textureless' appearance





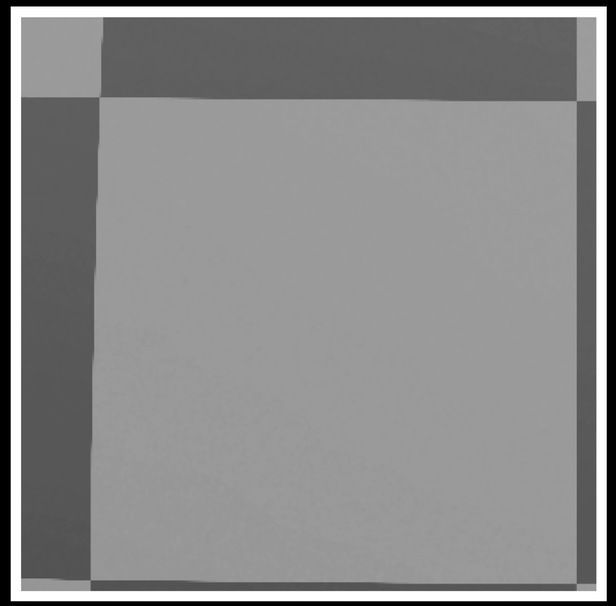
$$\sum_{M}\sum_{Q}$$

spectral spatial



speckle contributions

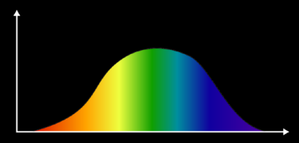
$=$

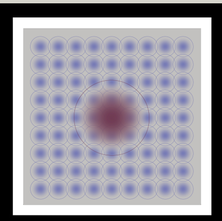


'textureless' appearance

$$\text{speckle strength} = \frac{1}{M\,Q}$$

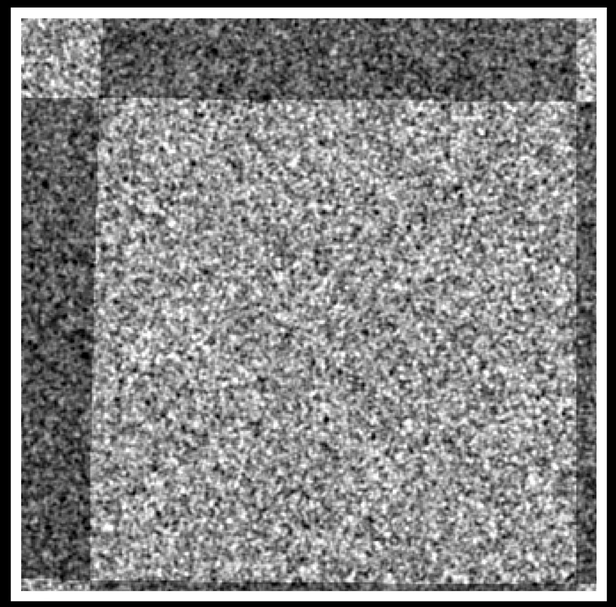
'textureless' appearance





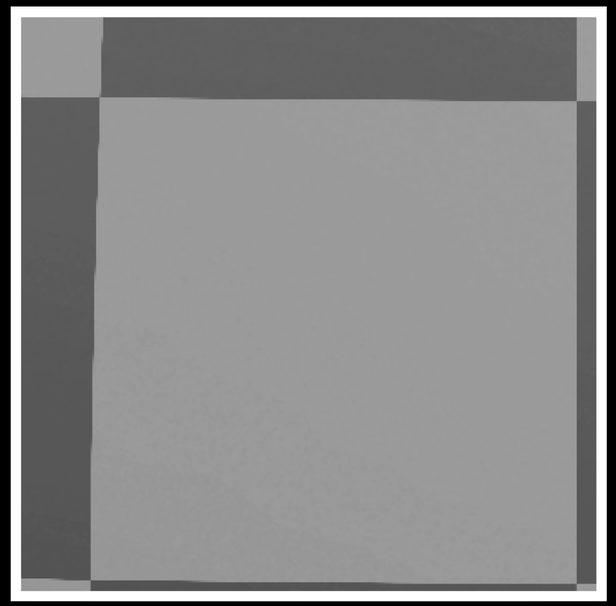
$$\sum_{M}\sum_{Q}$$

spectral spatial



speckle contributions

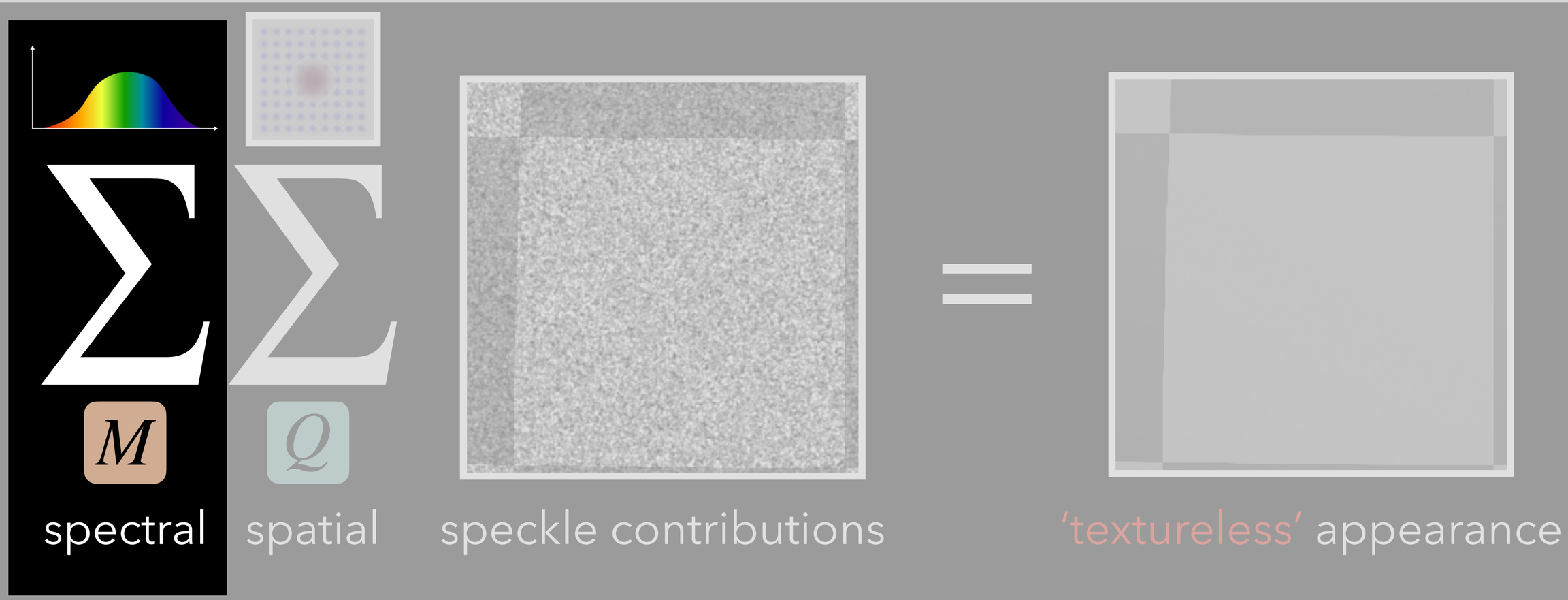
$=$



'textureless' appearance

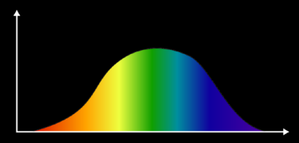
$$\text{speckle strength} = \frac{1}{M\,Q}$$

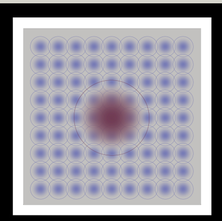
'textureless' appearance



$$\text{speckle strength} = \frac{1}{M\,Q}$$

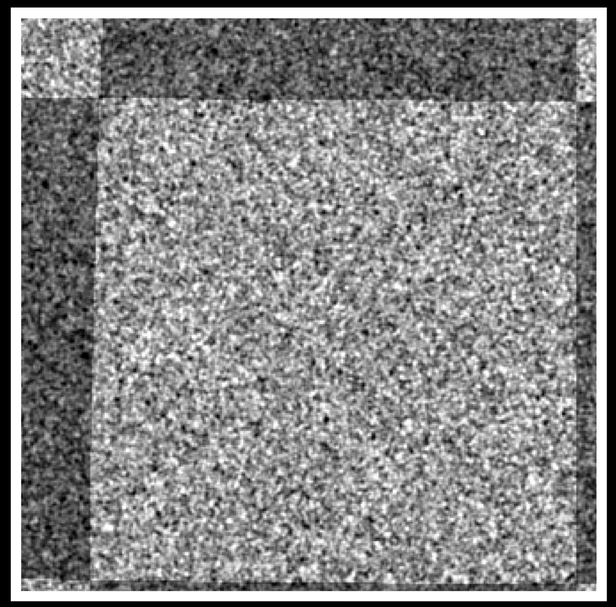
'textureless' appearance





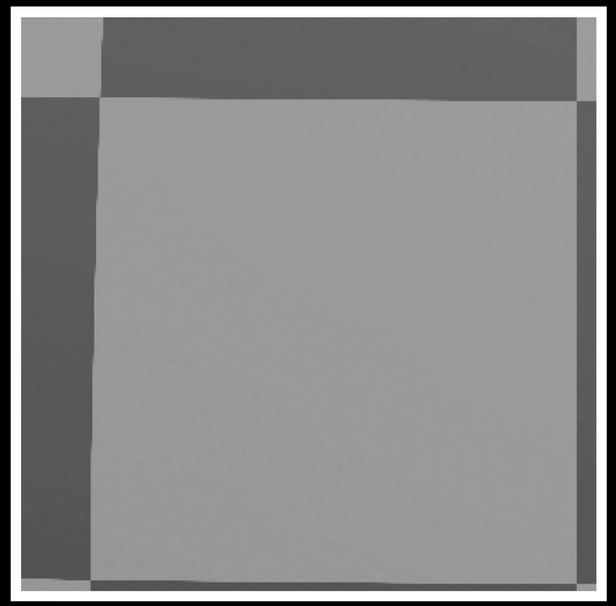
$$\sum_{M}\sum_{Q}$$

spectral spatial



speckle contributions

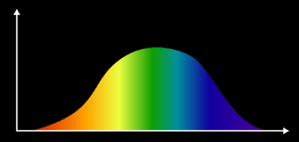
$=$

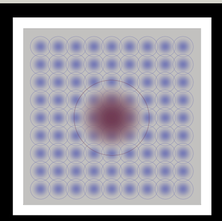


'textureless' appearance

$$\text{speckle strength} = \frac{1}{M\,Q}$$

'textureless' appearance

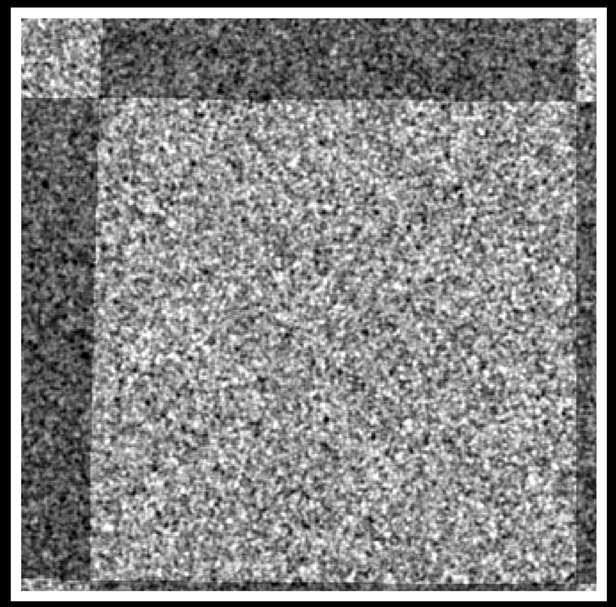




$$\sum \sum$$

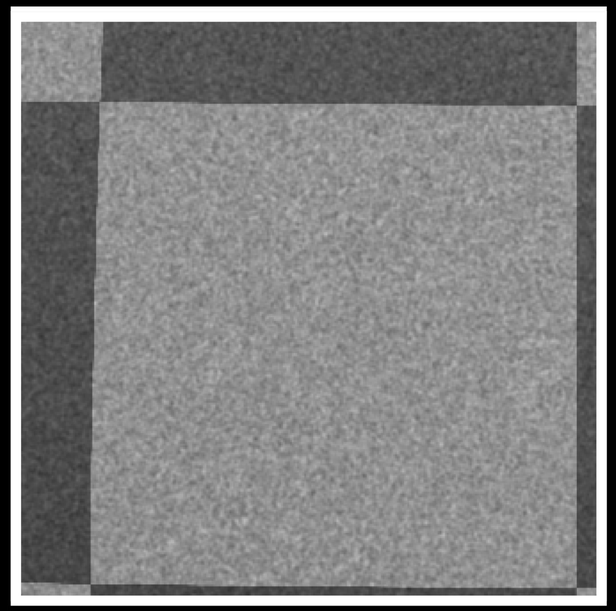
M Q

spectral spatial



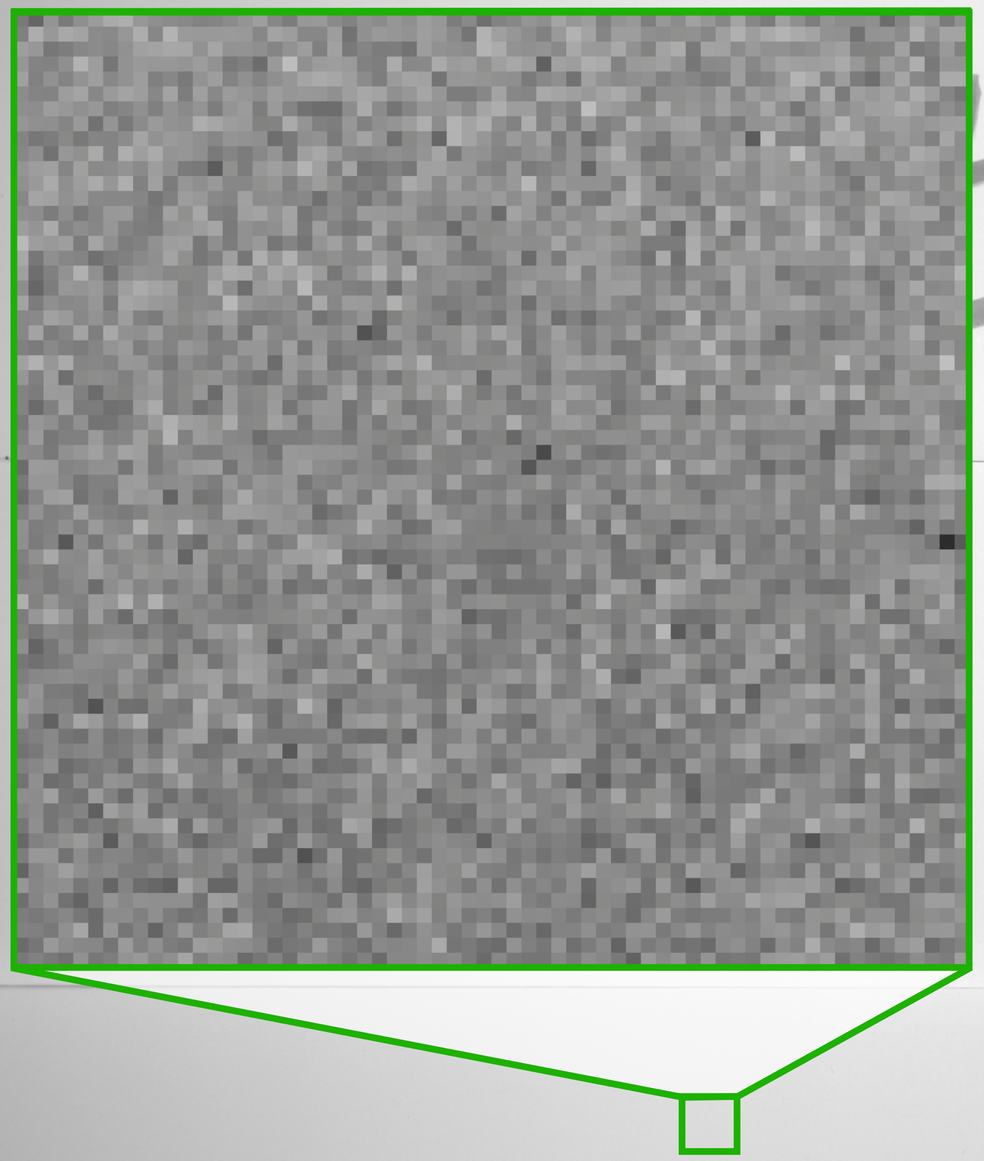
speckle contributions

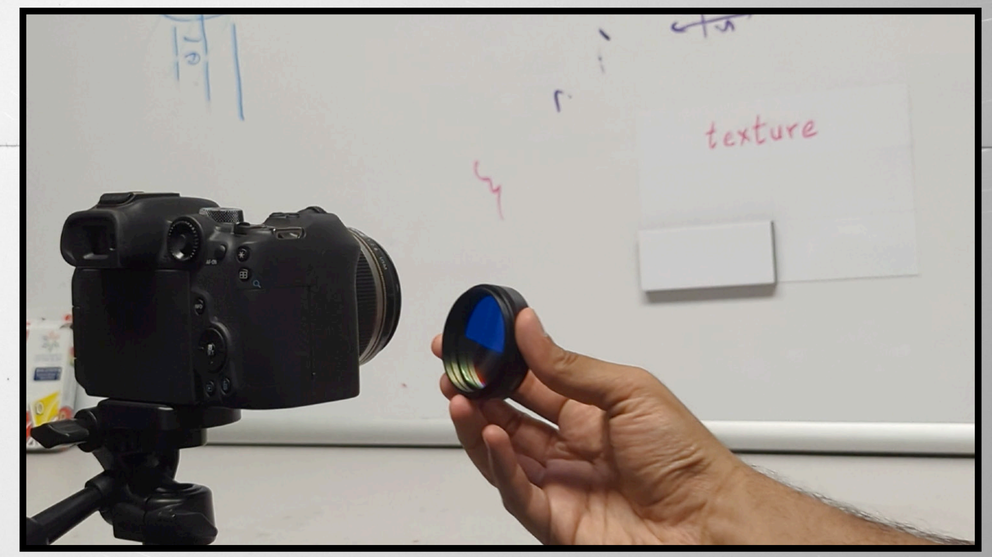
=

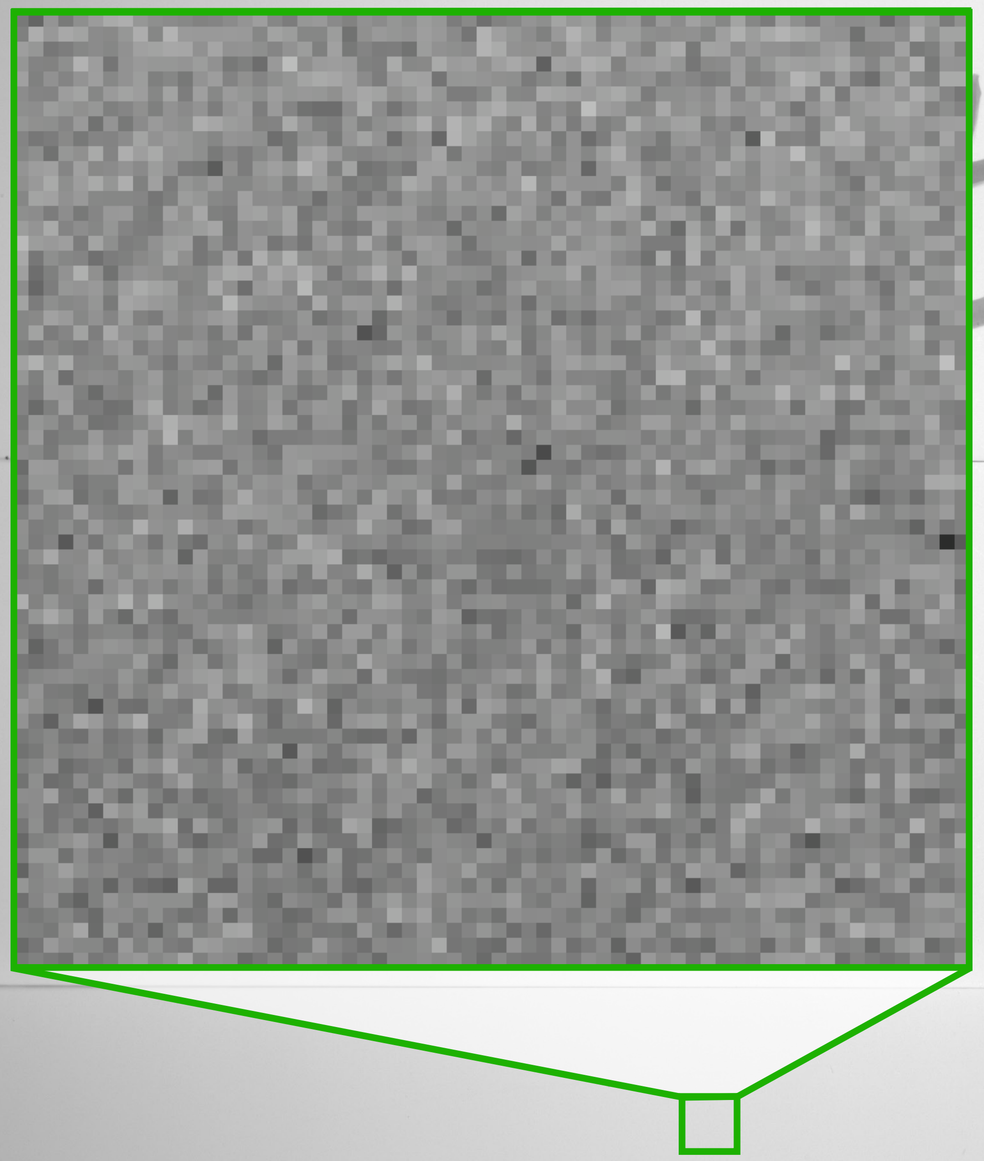


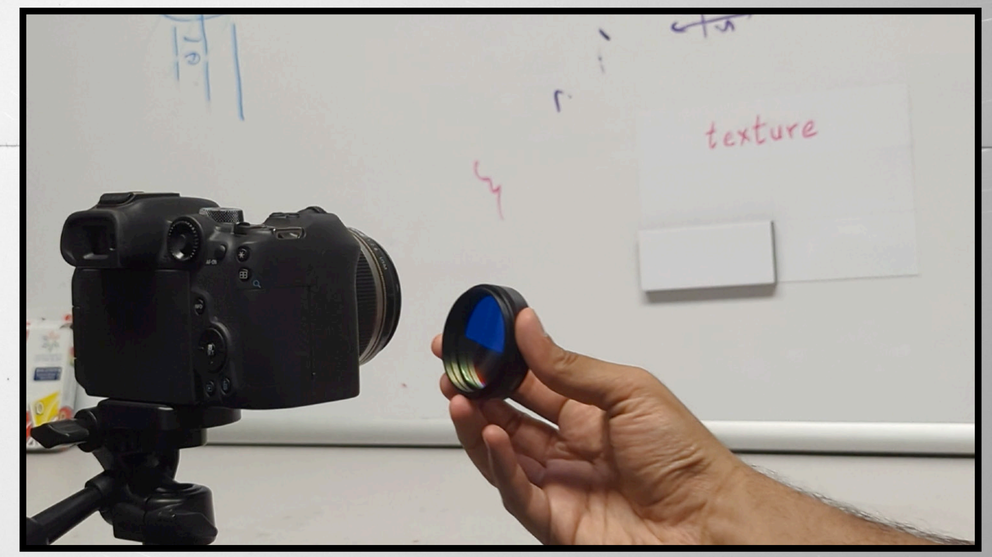
amplified speckle

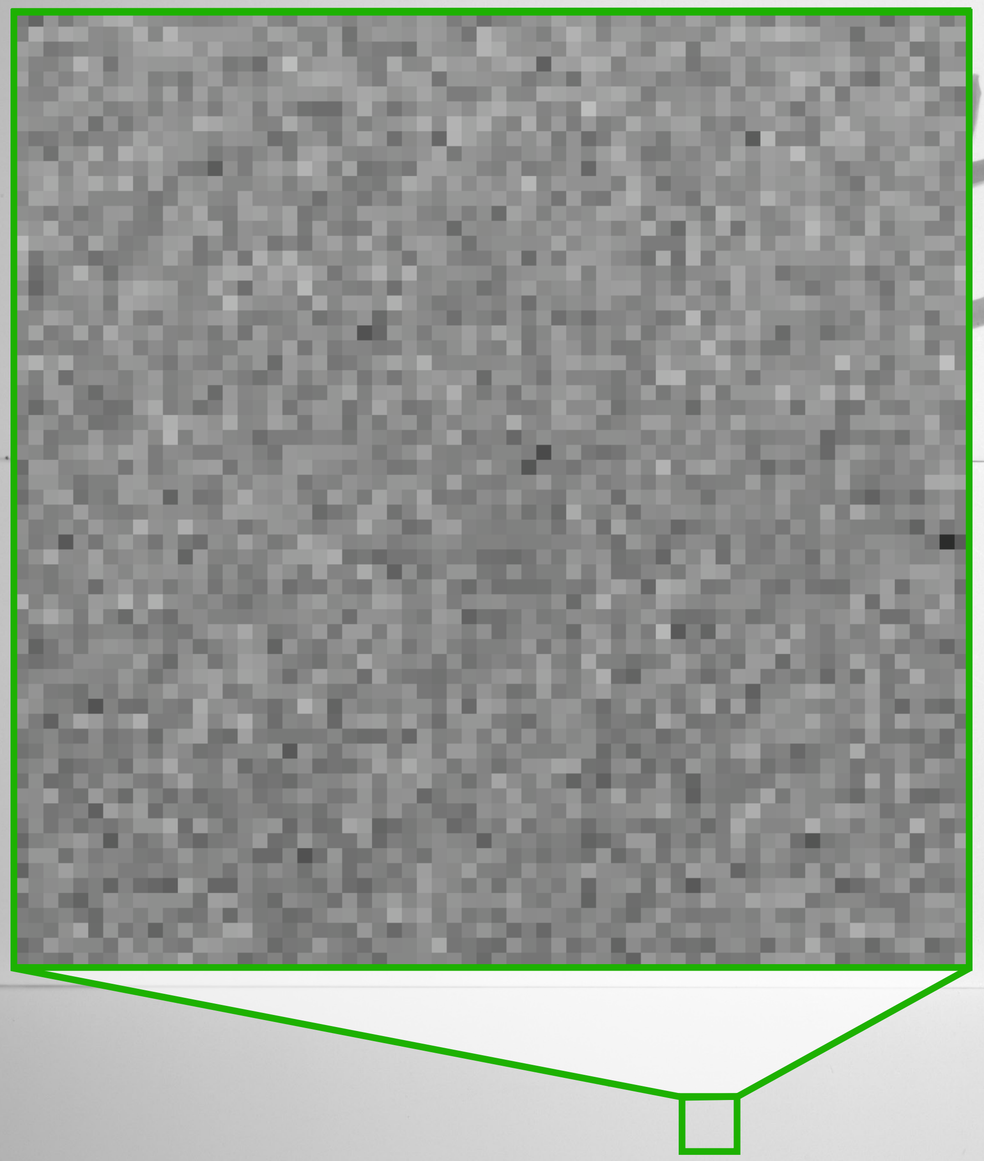
$$\text{speckle strength} = \frac{1}{M\,Q}$$

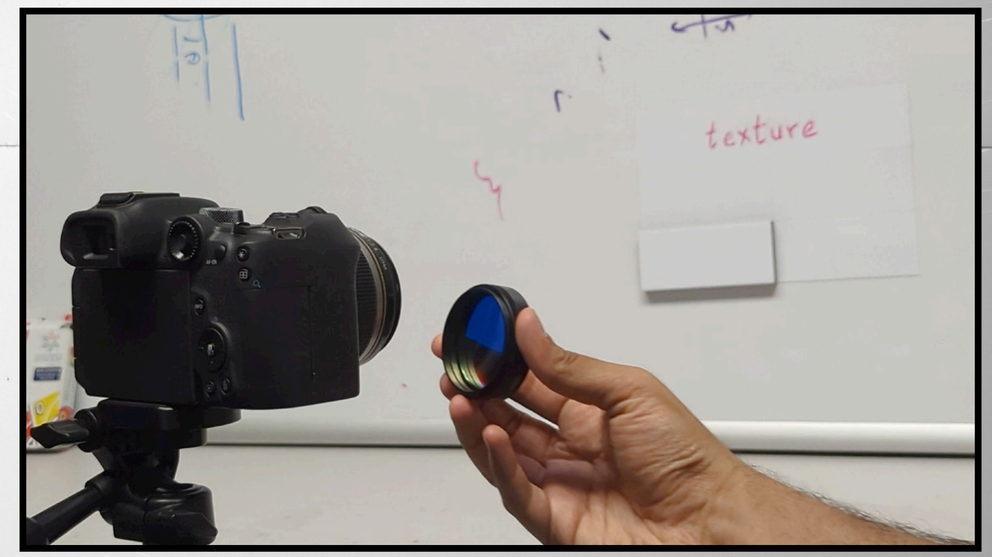



texture




texture

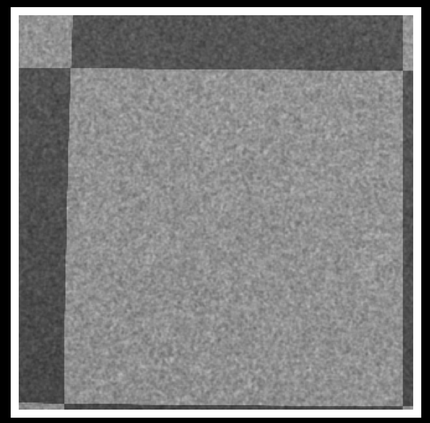




spectral filter amplifies
second-order *texture*

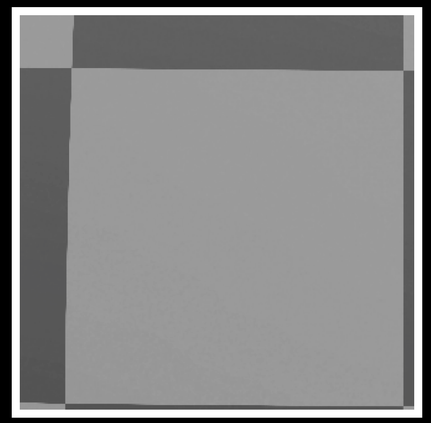
first and second-order texture

total texture



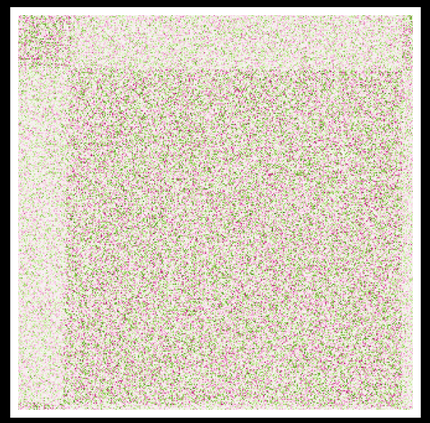
=

classical texture



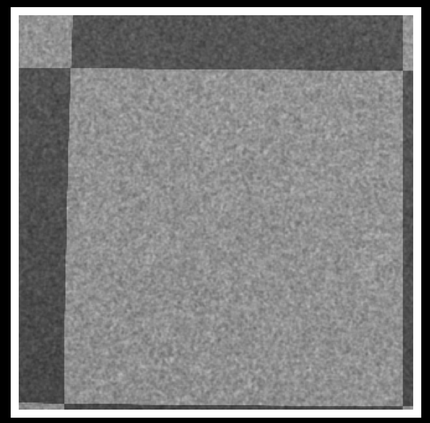
+

second-order texture



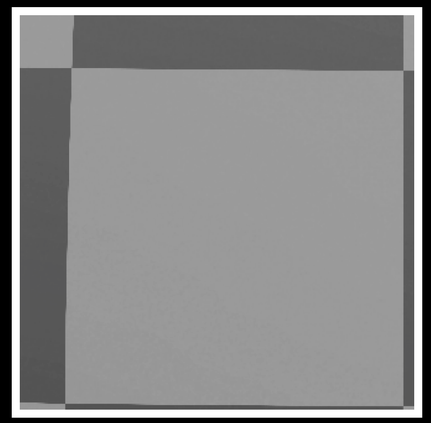
first and second-order texture

total texture



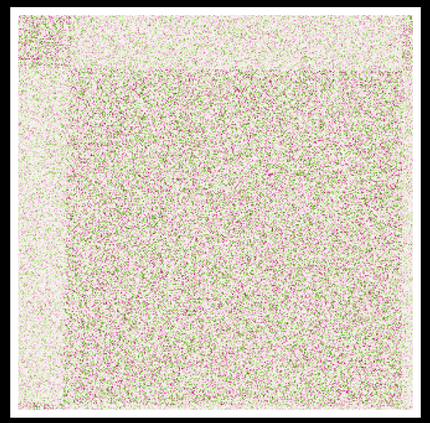
=

classical texture



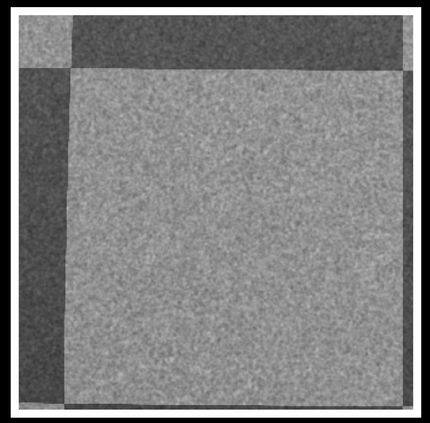
+

second-order texture



first and second-order texture

total texture



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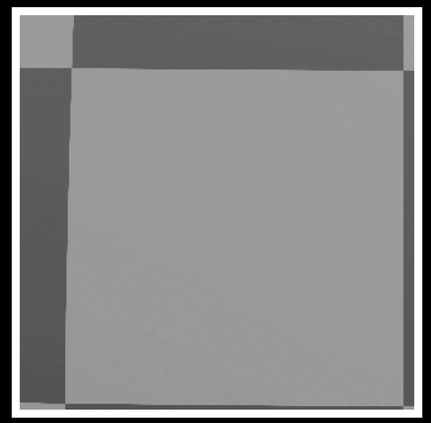
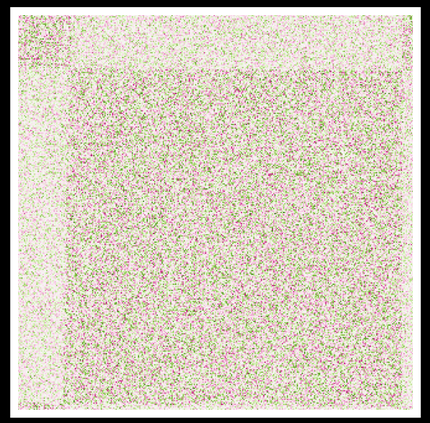
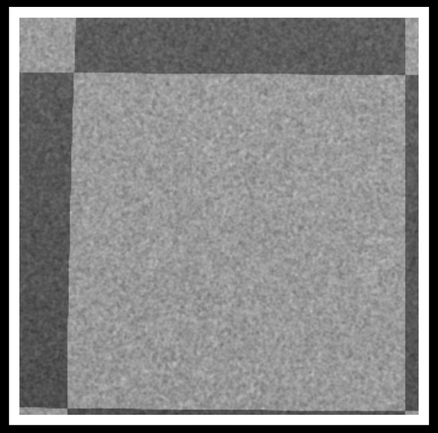
classical texture



+

second-order texture

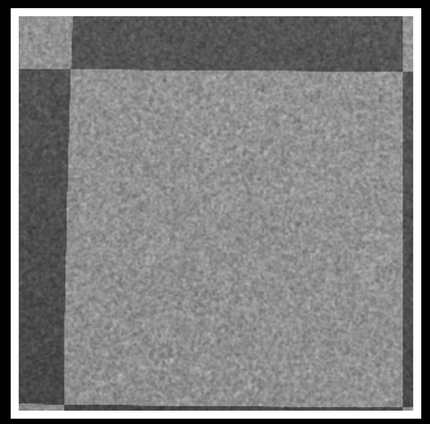


$\mathbb{E}$ []

first-order moment (mean)

first and second-order texture

total texture



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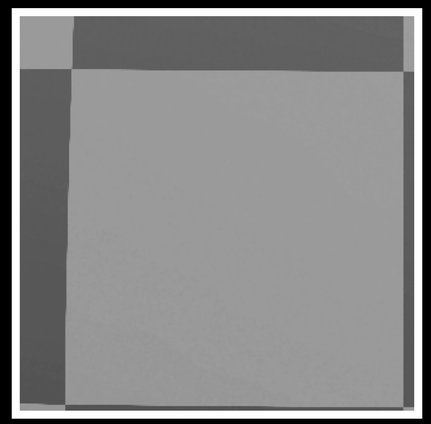
classical texture



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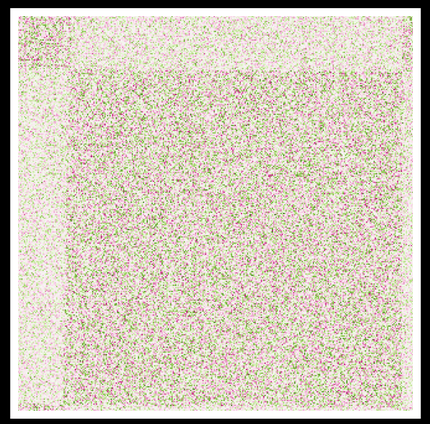
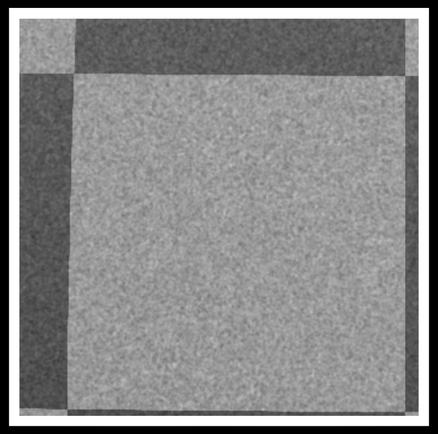
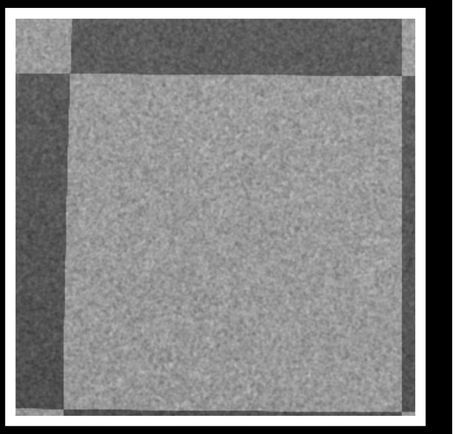
second-order texture



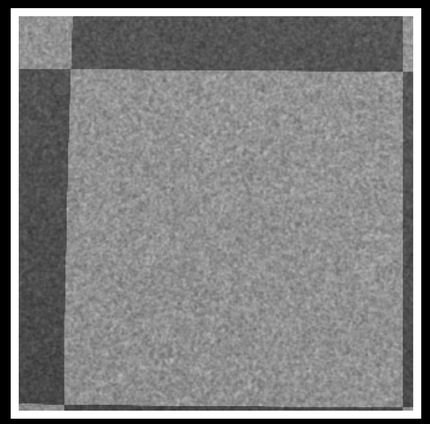
$\mathbb{E}\Big[$  $\Big]$ $\mathrm{Var}\Big[$  $\Big]$

first-order moment (mean)

second-order moment

first and second-order texture

total texture



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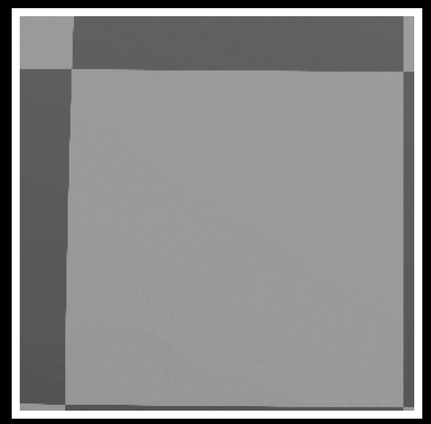
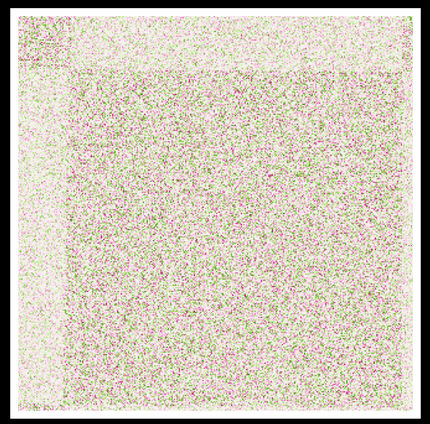
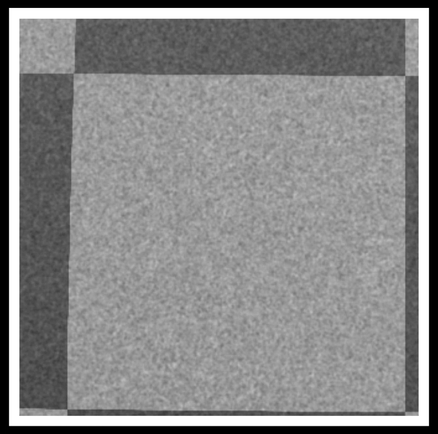
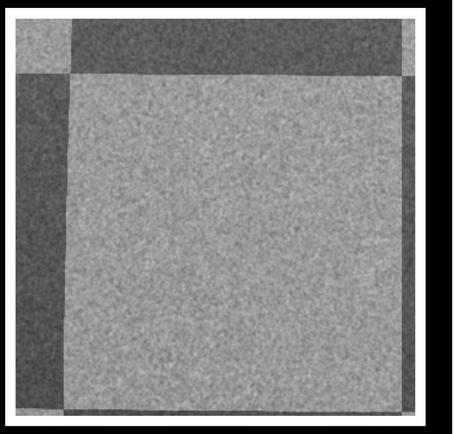
classical texture



+

second-order texture



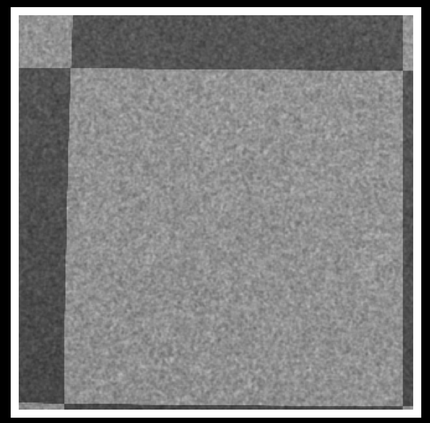
$\mathbb{E}\Big[$  $\Big]$ $\mathrm{Var}\Big[$  $\Big]$

first-order moment (mean)

second-order moment

first and second-order texture

total texture



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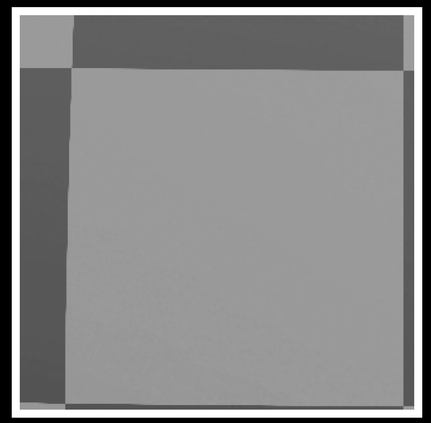
first-order texture



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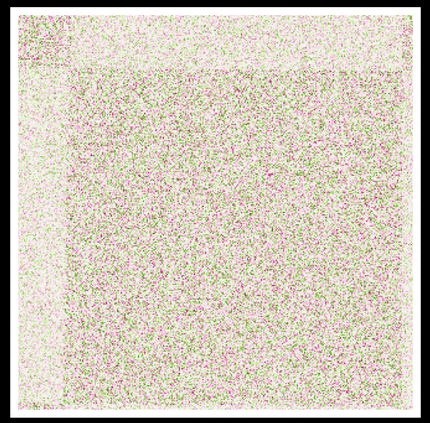
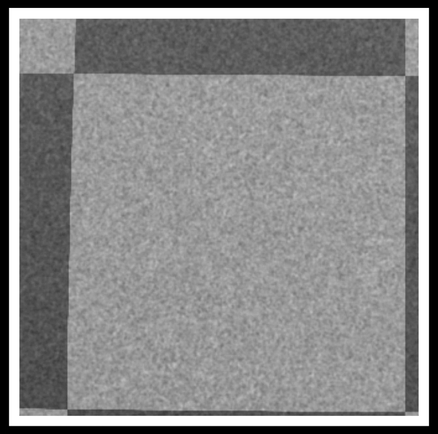
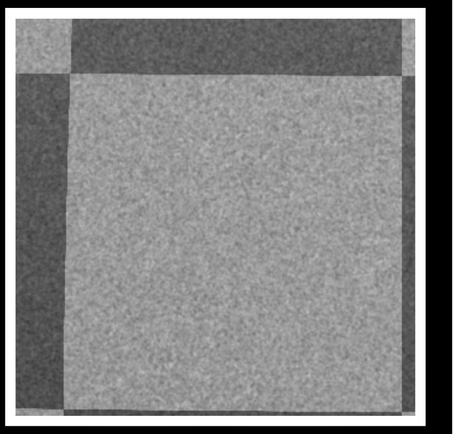
second-order texture



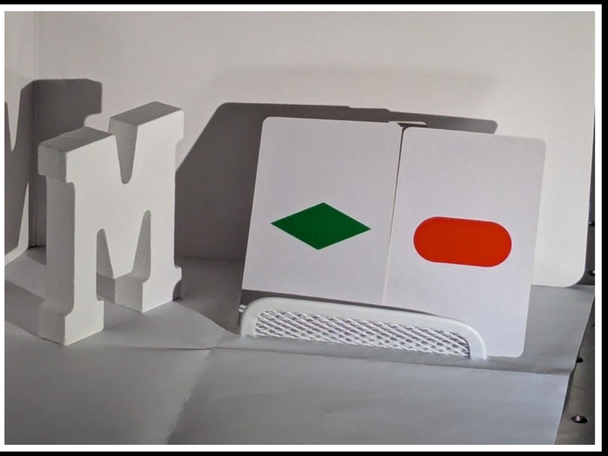
$\mathbb{E}\Big[$  $\Big]$ $\mathrm{Var}\Big[$  $\Big]$

first-order moment (mean)

second-order moment

indoor scene

raw image

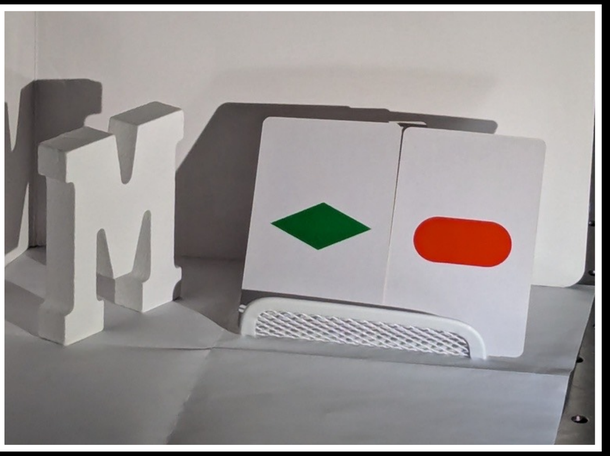


scene

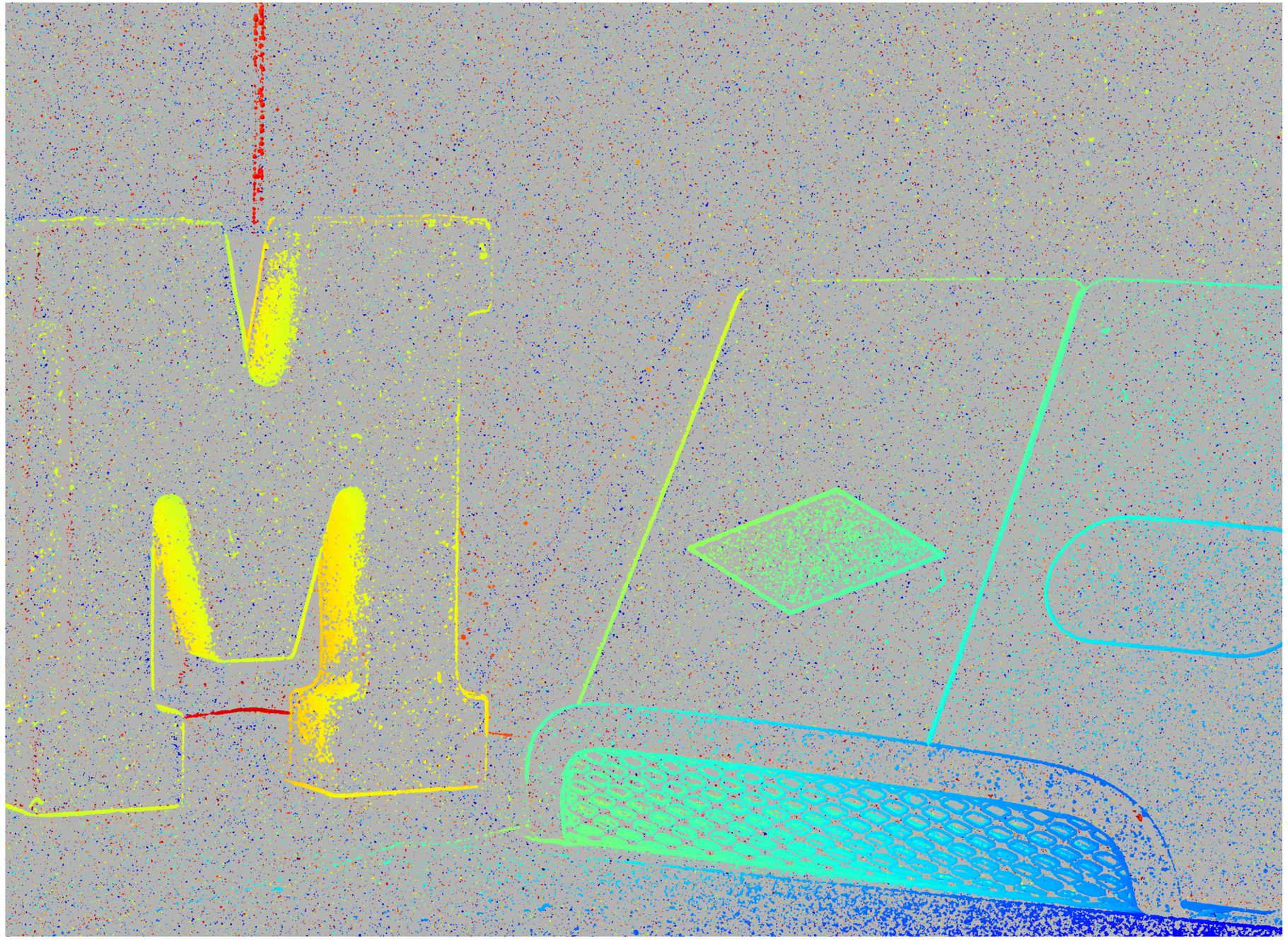
indoor scene

depth map

no filter



scene

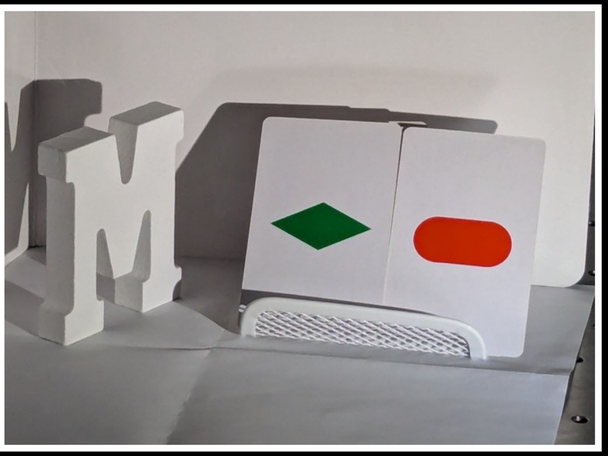


near far

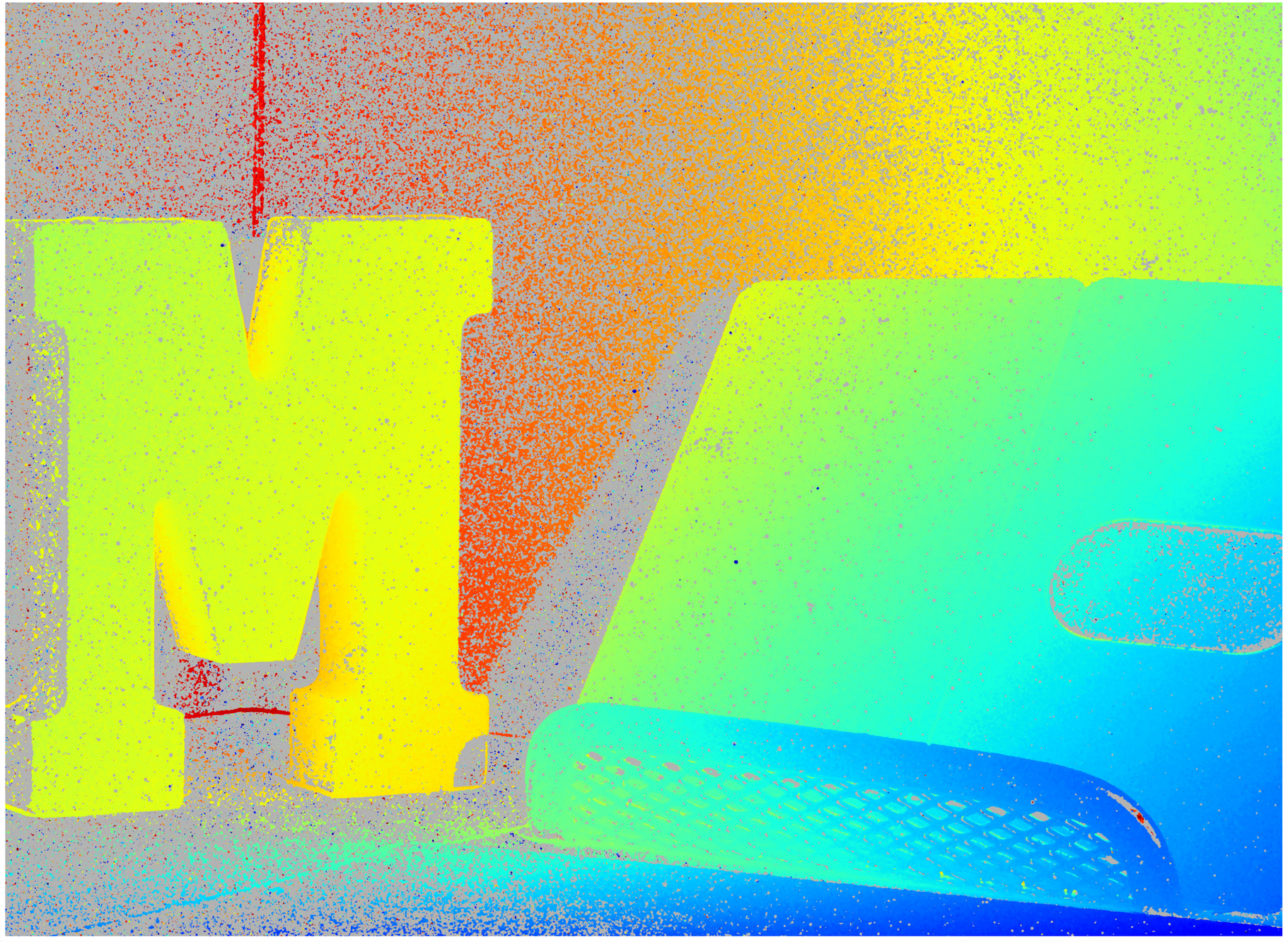
indoor scene

depth map

10 nm filter



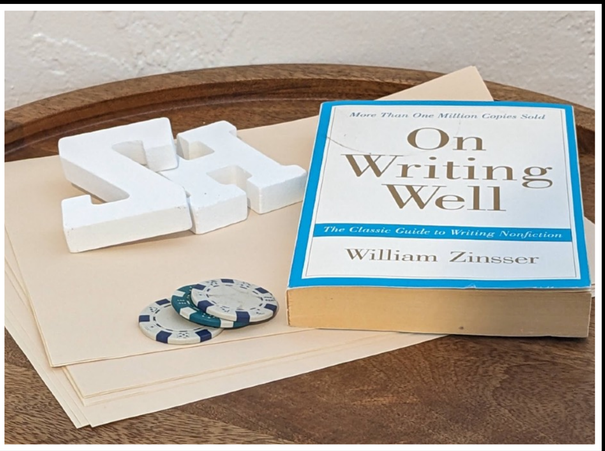
scene



near far

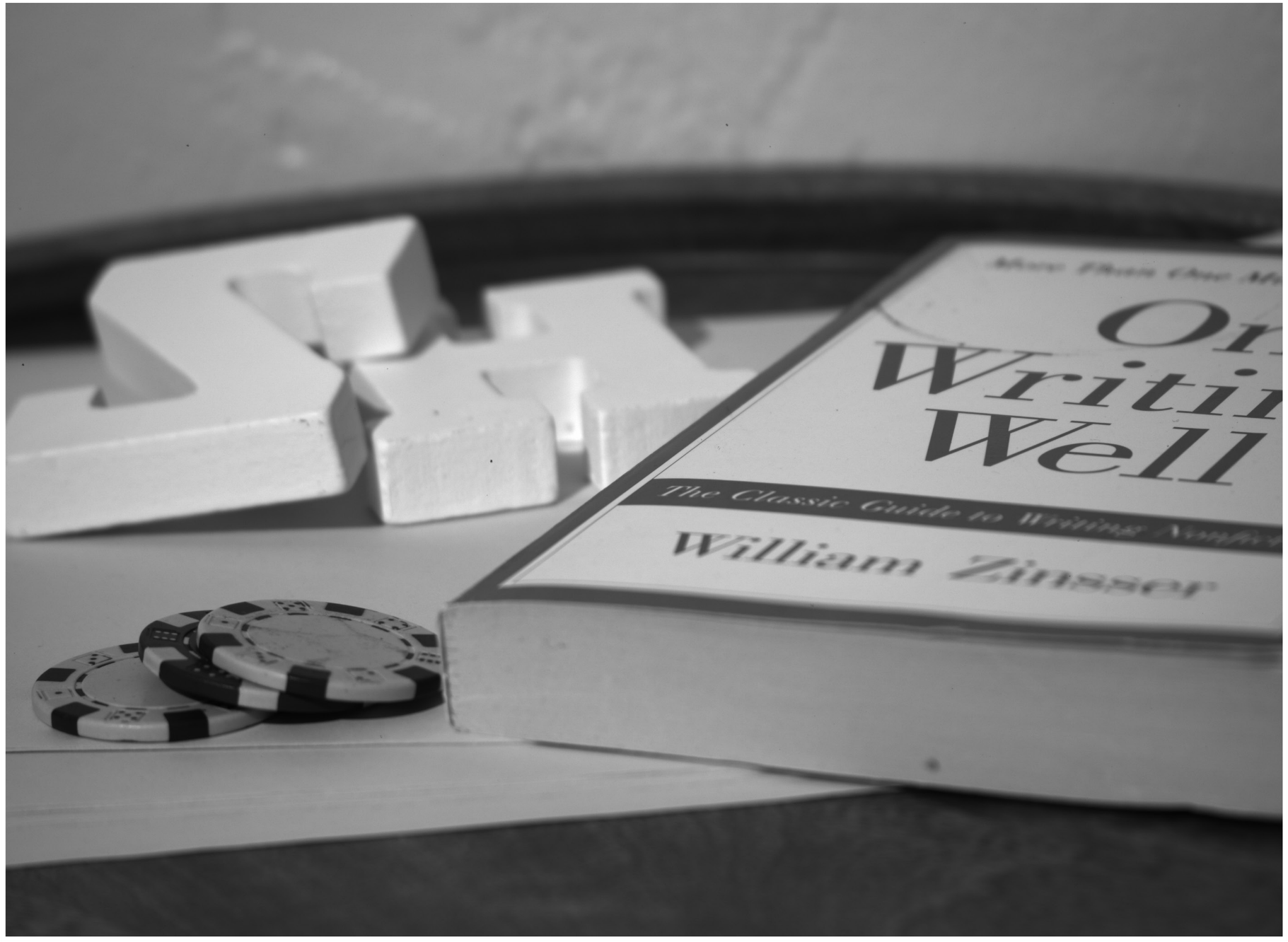
indoor scene

raw image



scene

lighting

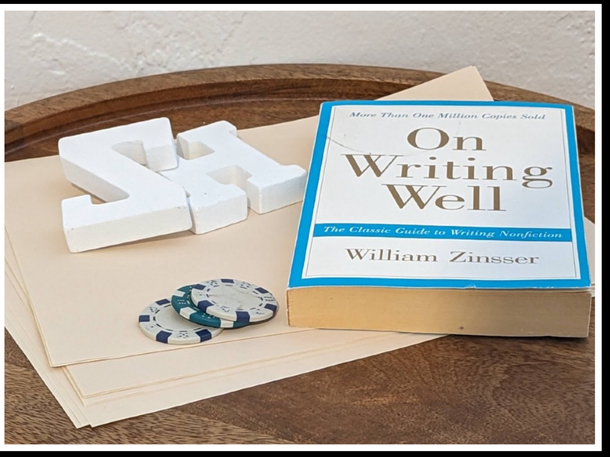


near far

indoor scene

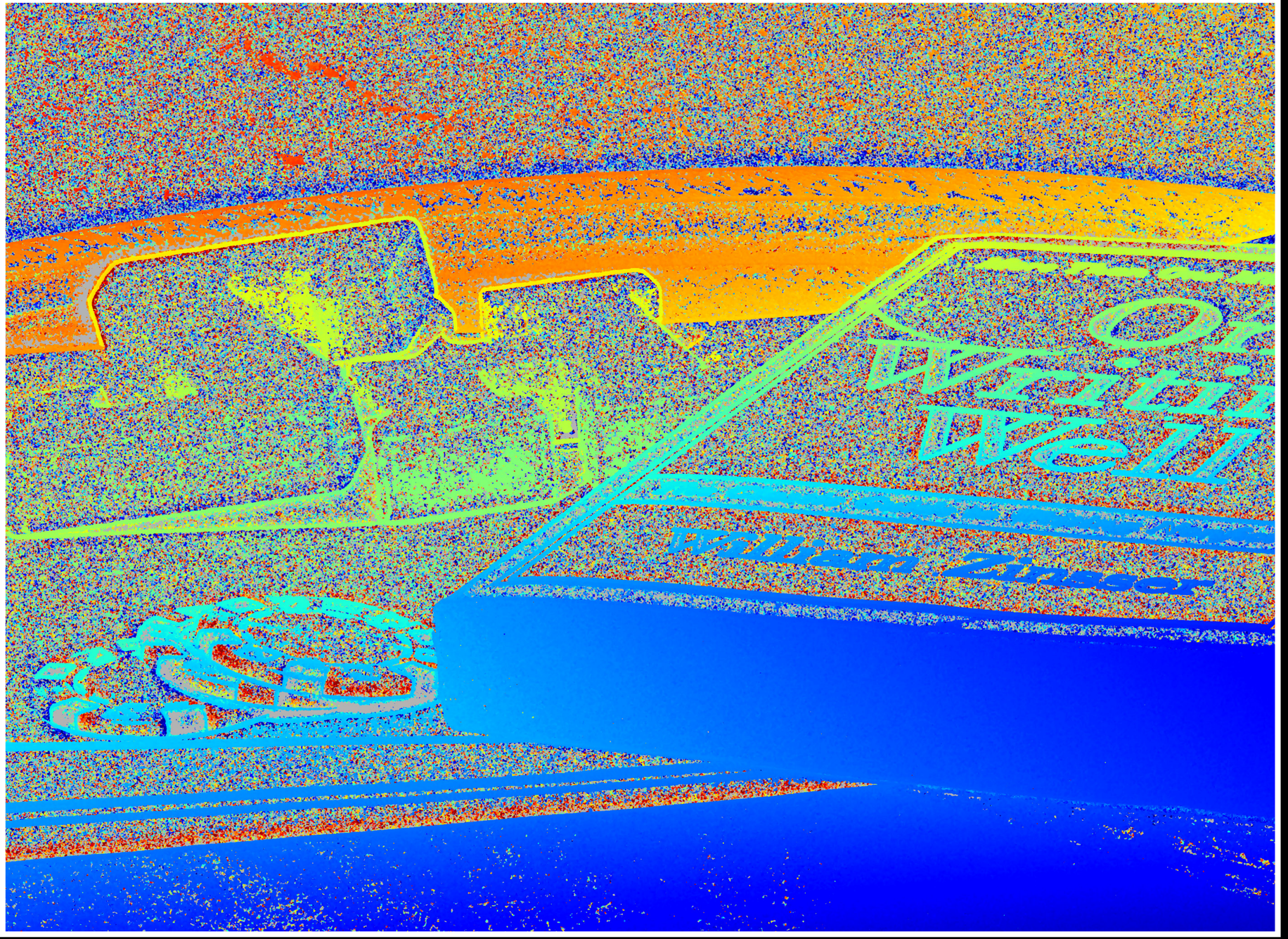
depth map

no filter



scene

lighting

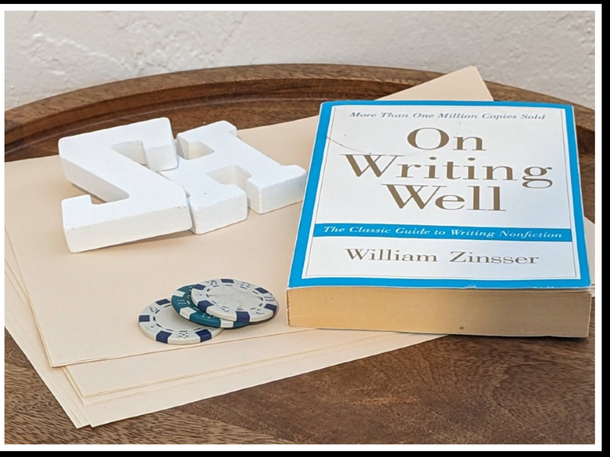


near far

indoor scene

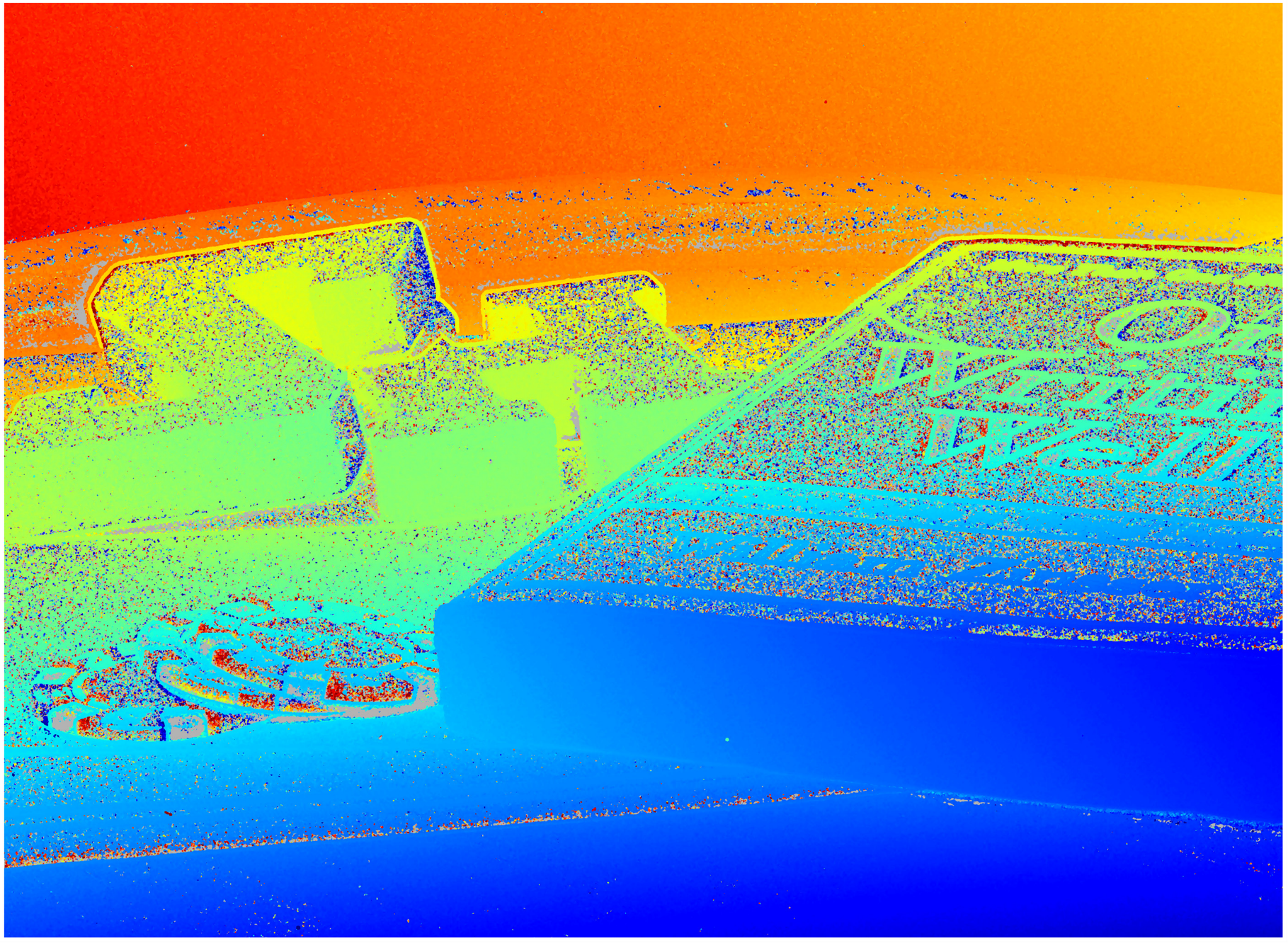
depth map

10 nm filter



scene

lighting



near far

outdoor scene

raw image

scene

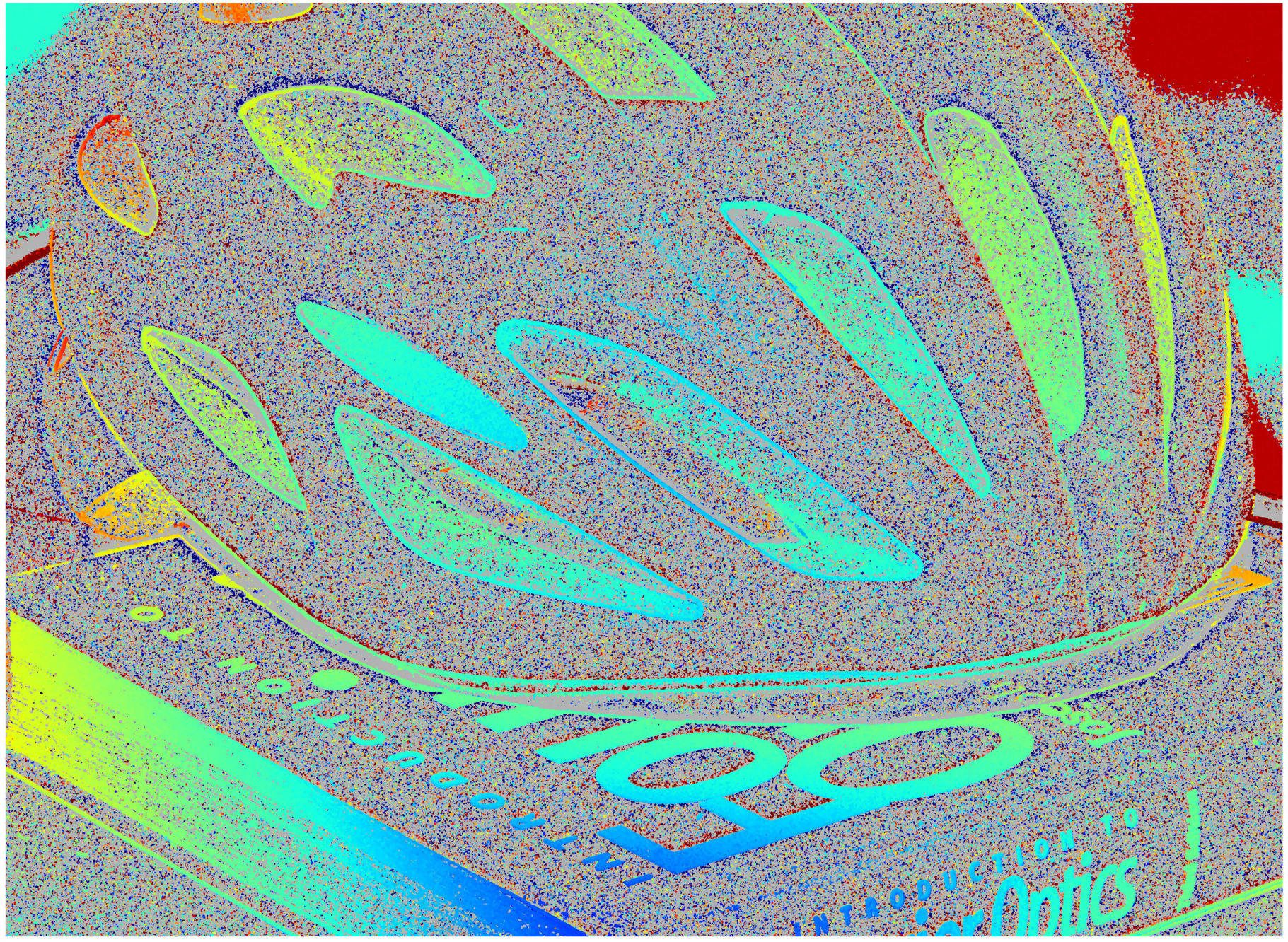
near far

outdoor scene

depth map

no filter

scene



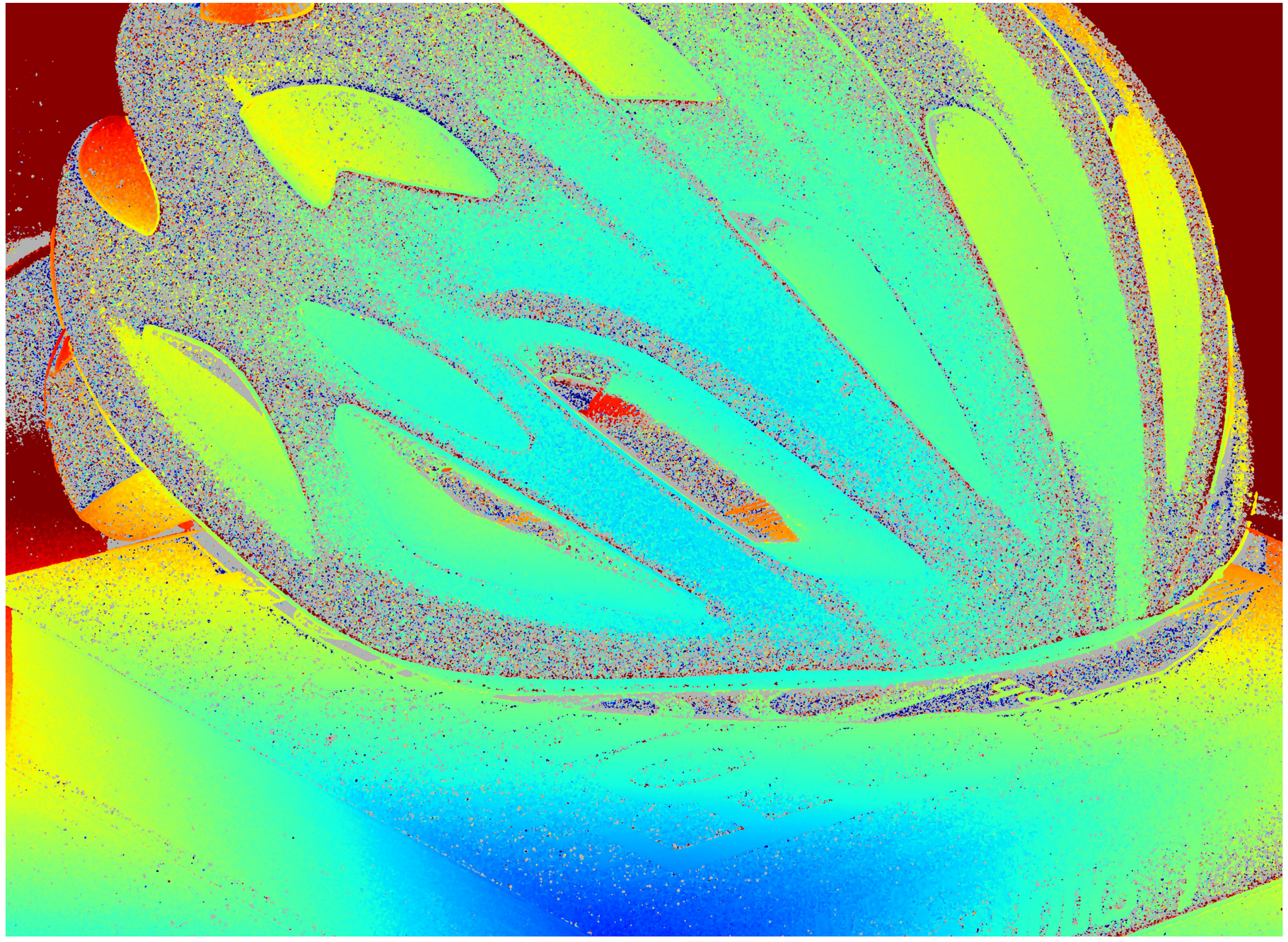
near far

outdoor scene

depth map

10 nm filter

scene



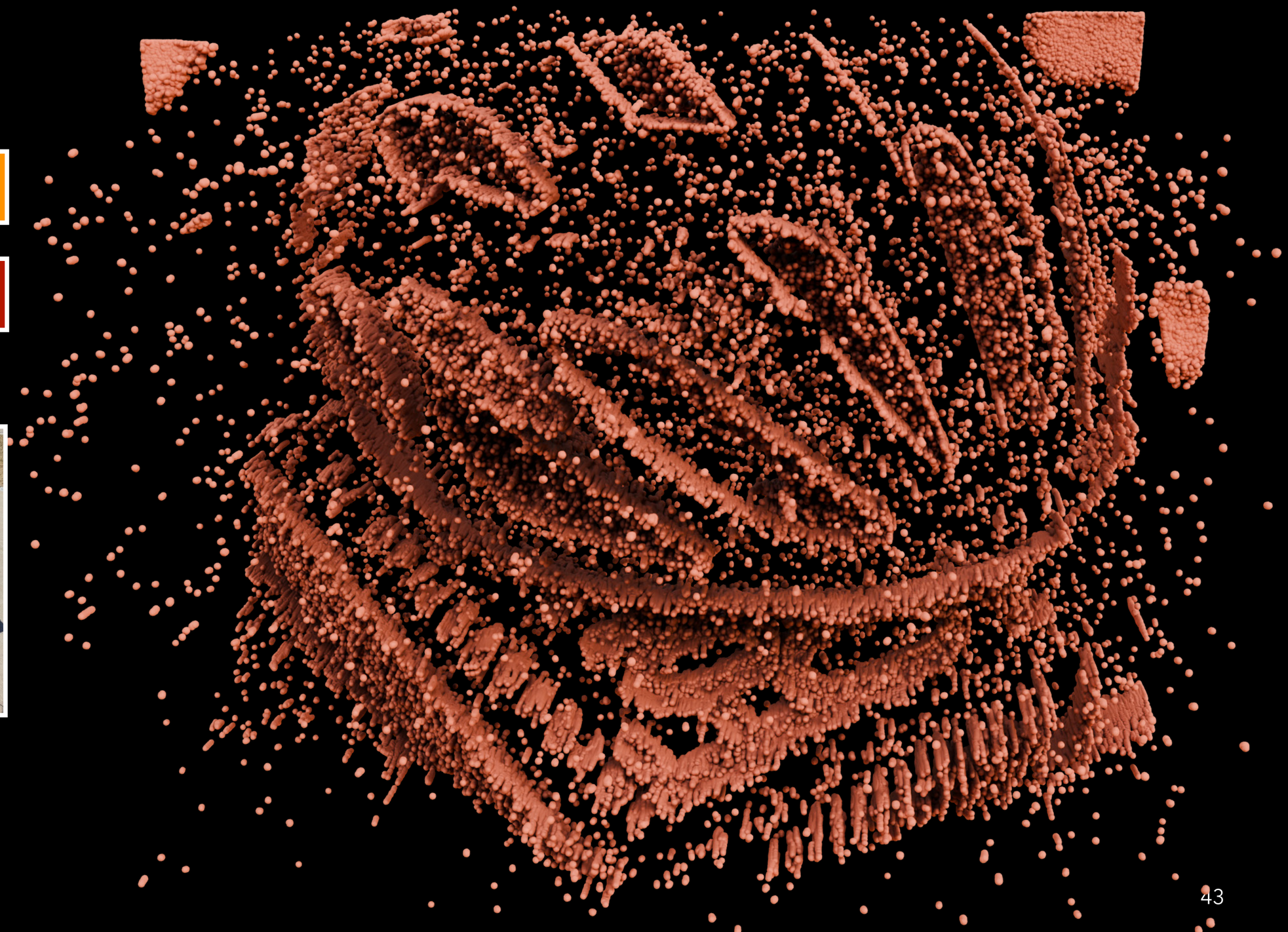
near far

outdoor scene

point cloud

no filter

scene

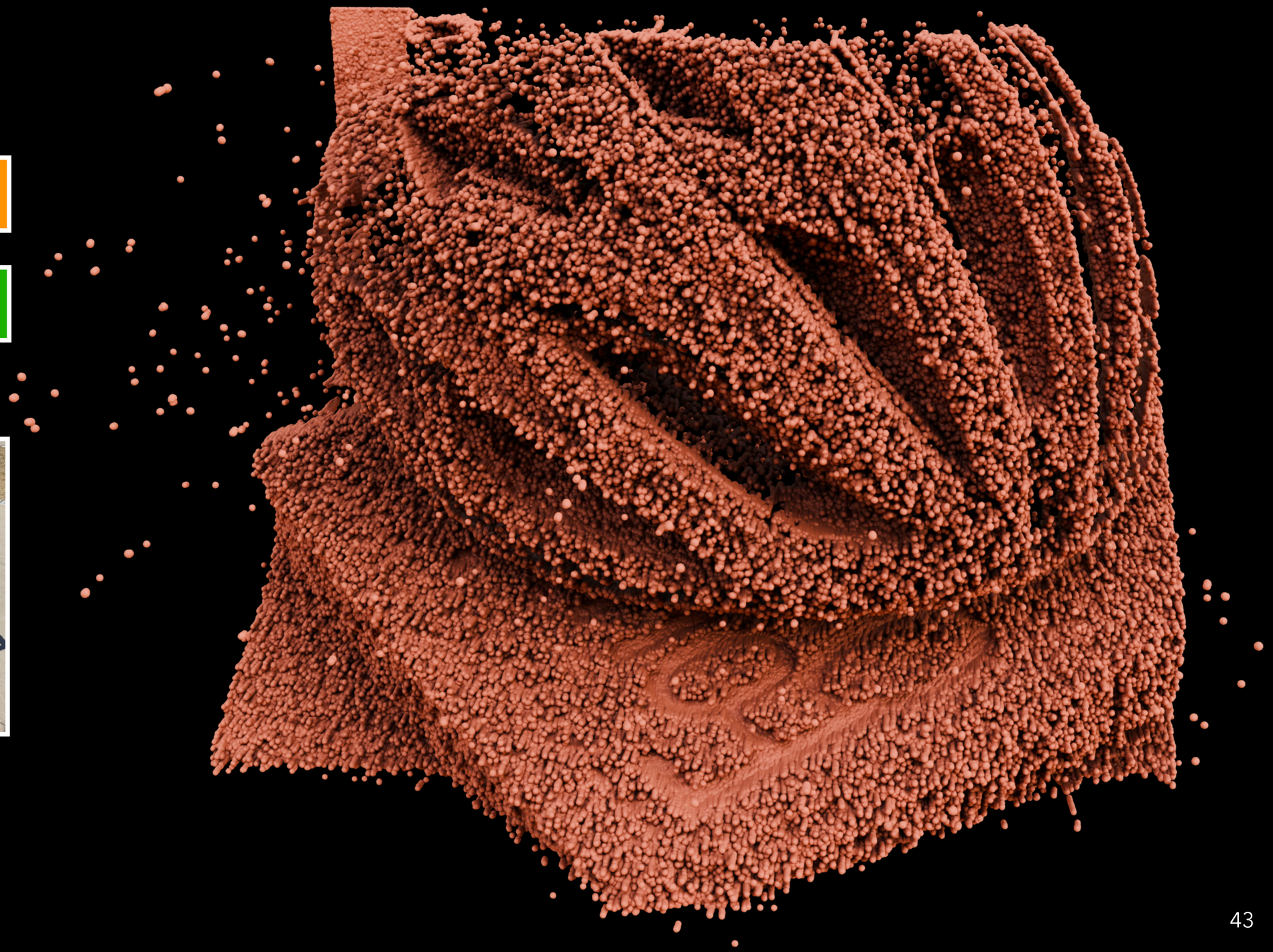


outdoor scene

point cloud

10 nm filter

scene



outdoor scene

raw image

scene

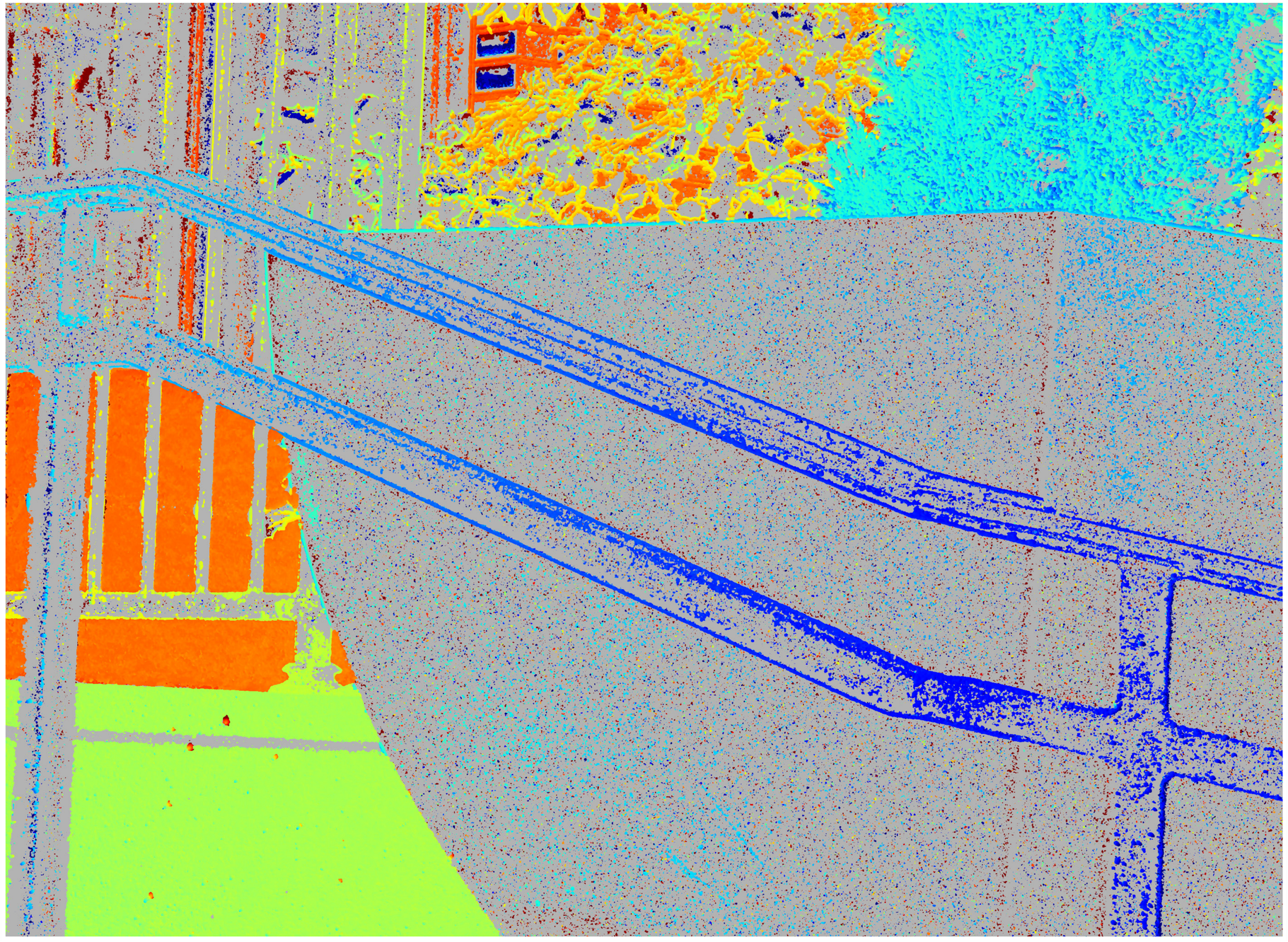
near far

outdoor scene

depth map

no filter

scene



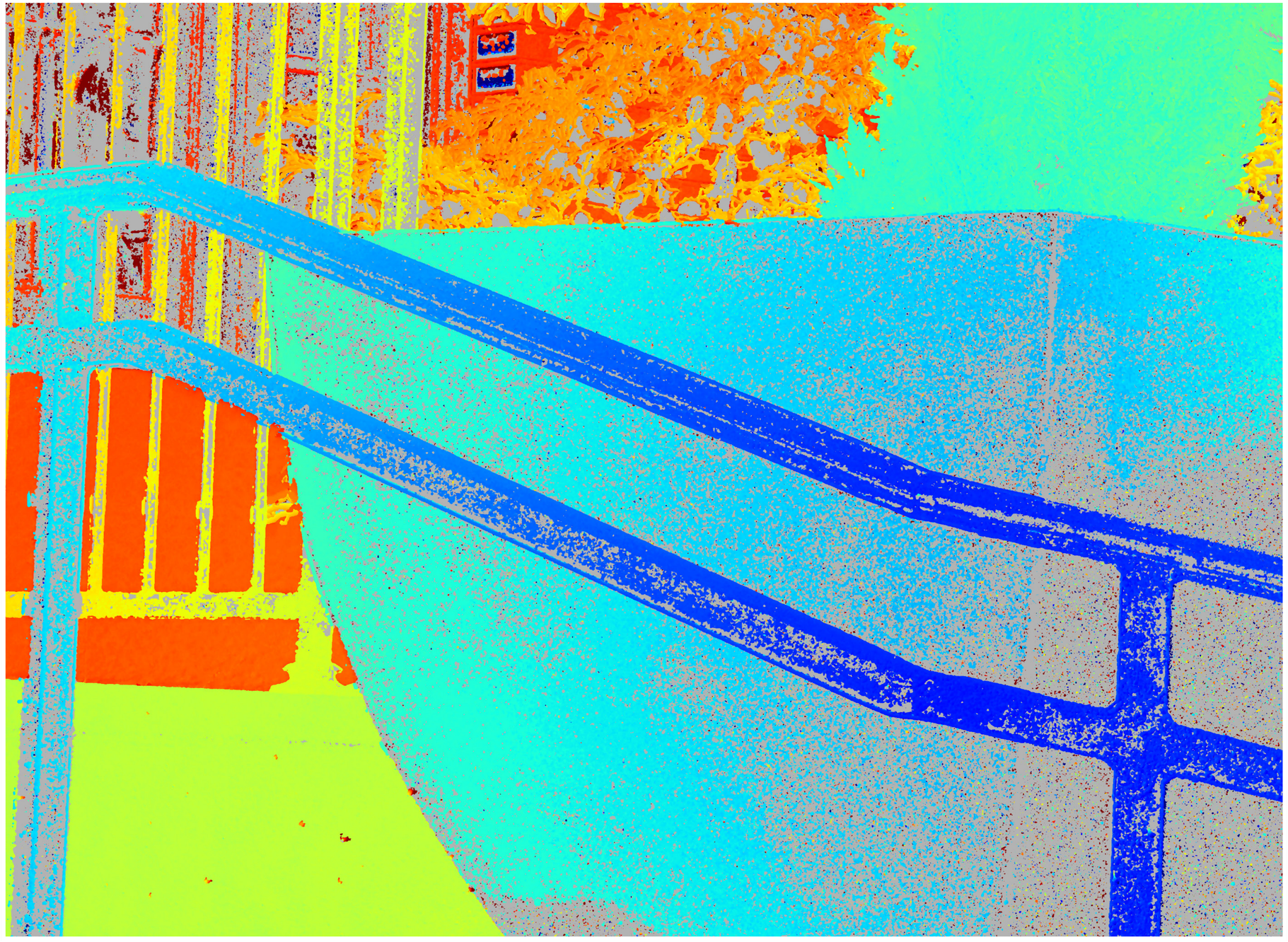
near far

outdoor scene

depth map

10 nm filter

scene



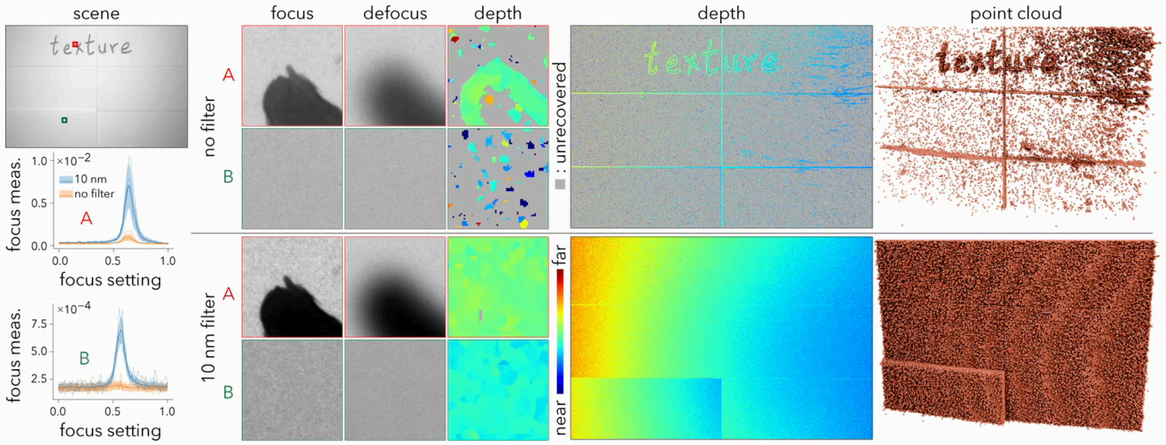
near far

A second-order theory of texture for depth from focus

Sreekar Ranganathan, Ioannis Gkioulekas

ECCV 2026

visualization paper code data citation

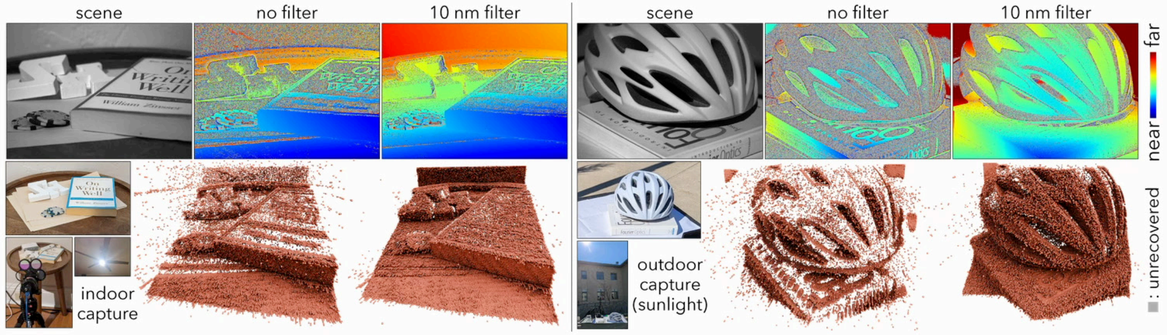


Computer vision traditionally considers depth recovery of scenes with sparse texture features impossible with passive methods such as depth from focus (top). We show that simply adding a narrowband spectral filter to the camera makes passive depth recovery of such scenes possible (bottom). We explain this surprising finding by developing a theory of second-order texture—a form of subjective speckle whose in-focus contrast is enhanced with decreasing spectral bandwidth (crops to the left).

Abstract

We present a theory of textured appearance of optically rough surfaces based on wave optics, emphasizing the role of texture for passive depth from focus. Our theory shows that even surfaces that traditional computer vision would consider textureless can produce textured appearance, due to subjective speckle from surface microgeometry. We analyze the properties of this *second-order texture*, and show that we can enhance its contrast under natural ambient lighting by simply using a narrowband spectral filter. Doing so results in dramatic improvements in passive depth reconstruction of seemingly textureless scenes, as we demonstrate through extensive theory, simulations, and real-world experiments.

Robustness to illumination conditions

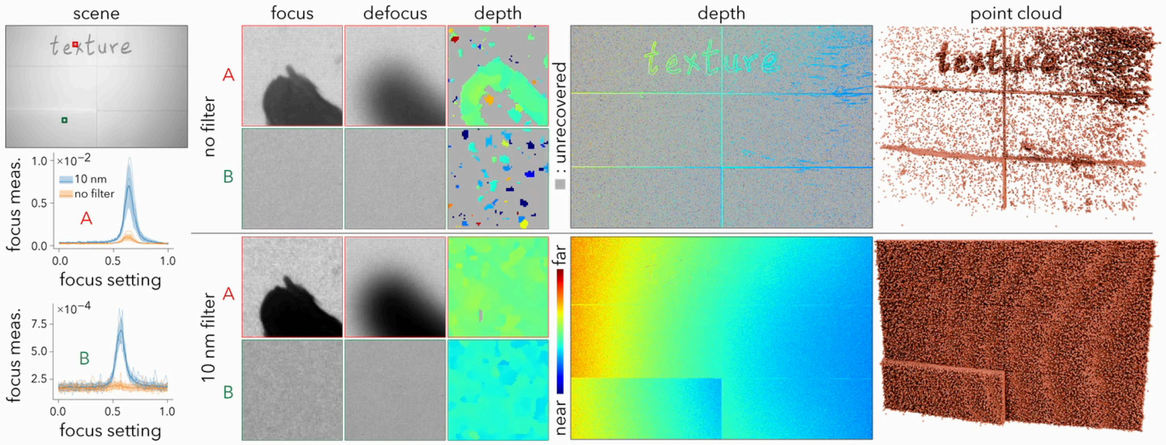


A second-order theory of texture for depth from focus

Sreekar Ranganathan, Ioannis Gkioulekas

ECCV 2026

visualization paper code data citation



Computer vision traditionally considers depth recovery of scenes with sparse texture features impossible with passive methods such as depth from focus (top). We show that simply adding a narrowband spectral filter to the camera makes passive depth recovery of such scenes possible (bottom). We explain this surprising finding by developing a theory of second-order texture—a form of subjective speckle whose in-focus contrast is enhanced with decreasing spectral bandwidth (crops to the left).

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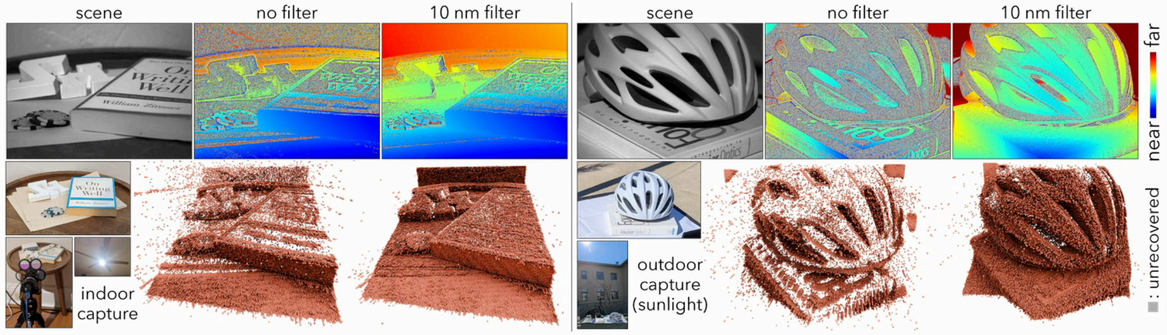
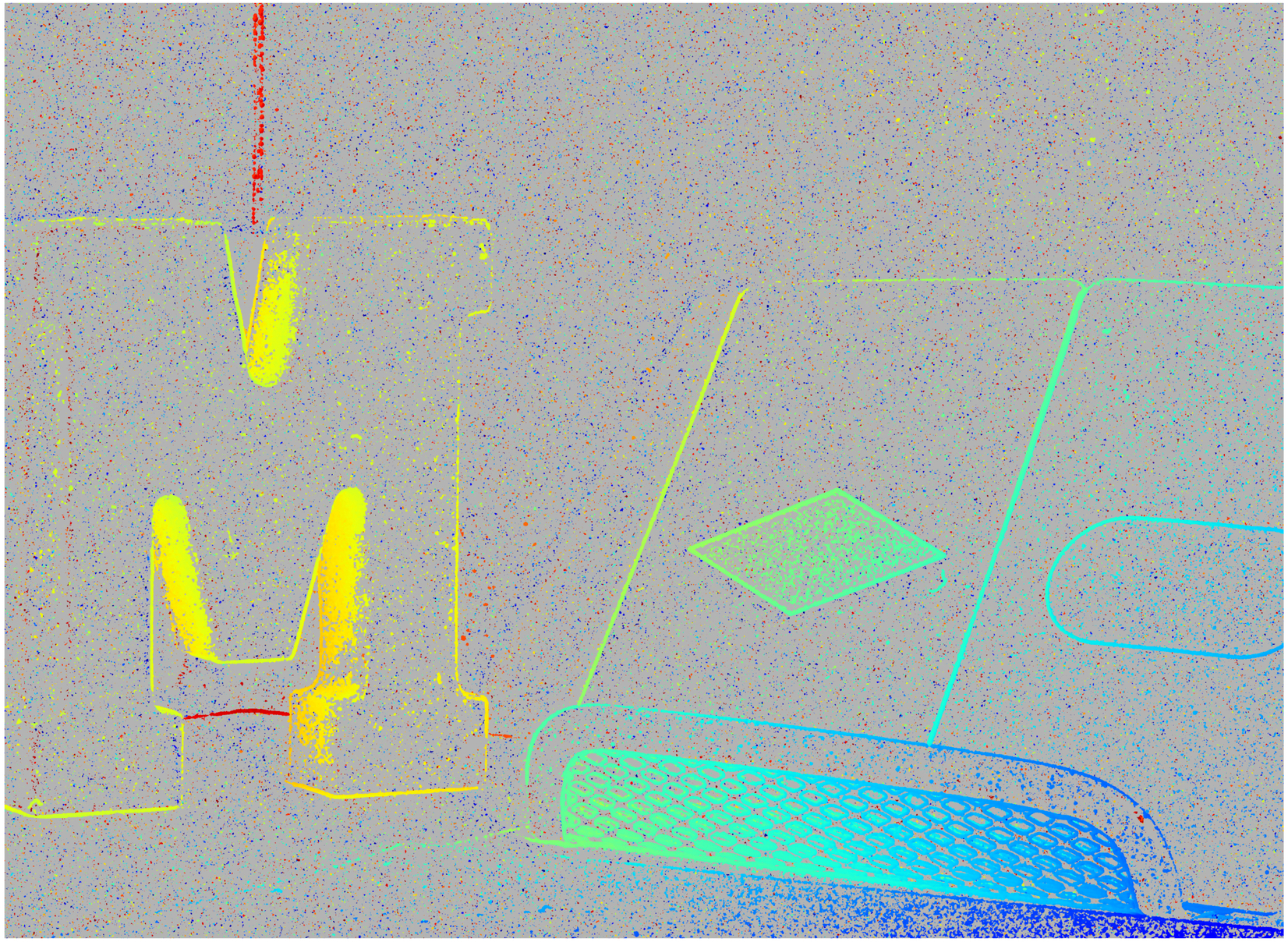
Robustness to illumination conditions



the texture-SNR tradeoff

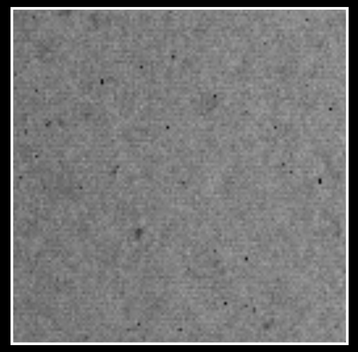


no filter

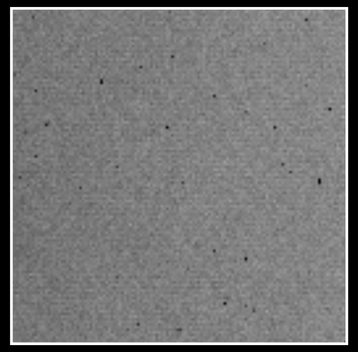
properly exposed

1x exposure time

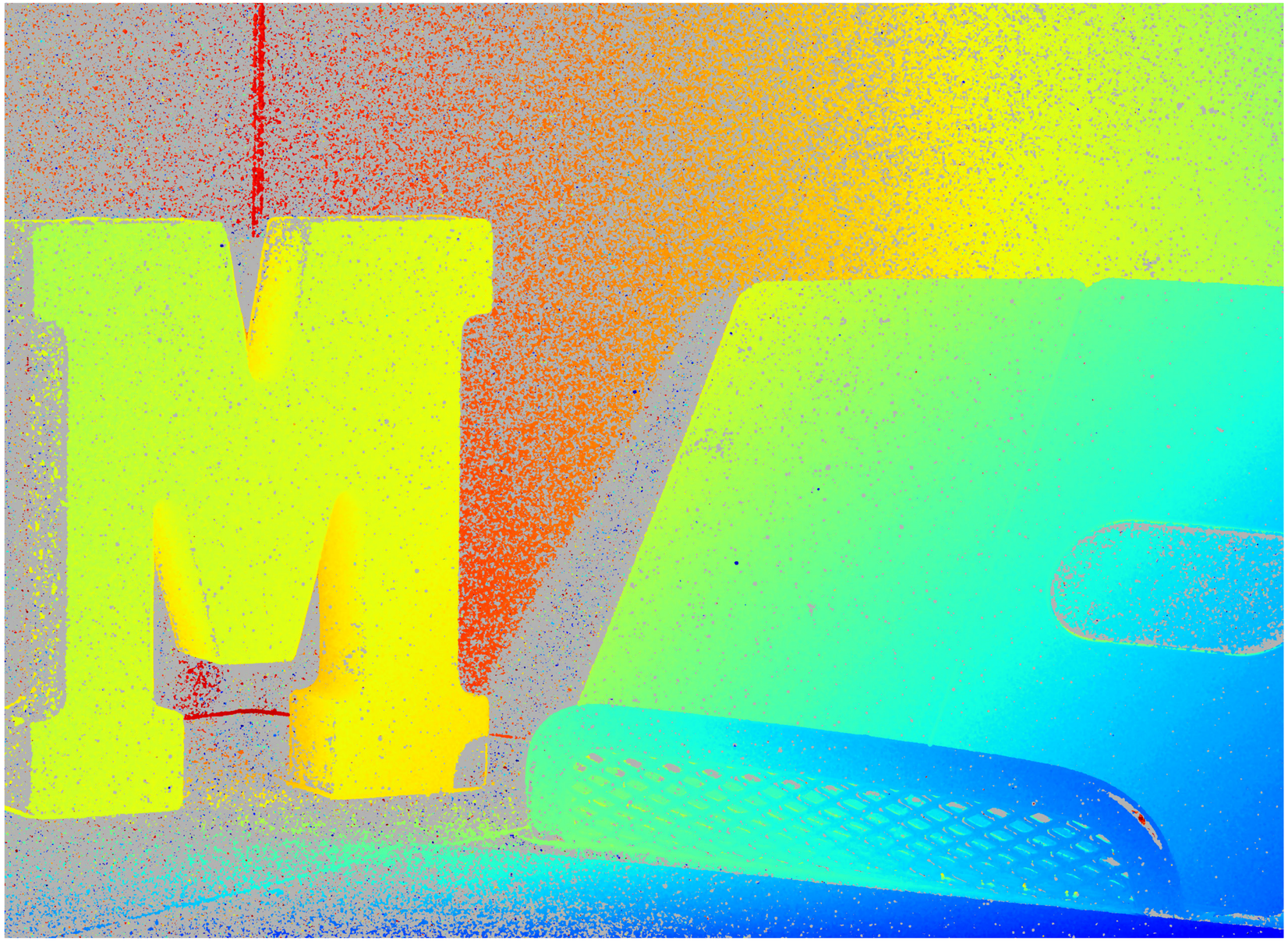
in-focus



defocused



the texture-SNR tradeoff

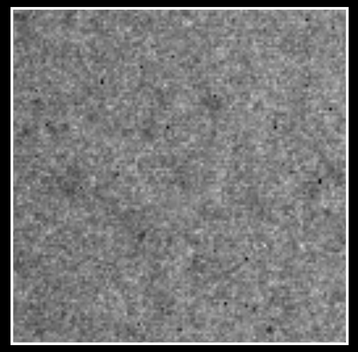


10 nm filter

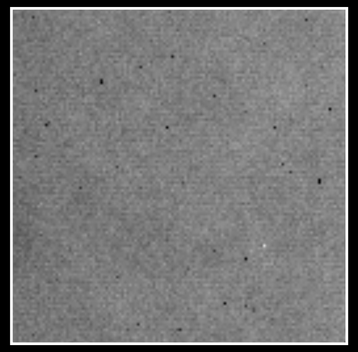
properly exposed

32x exposure time

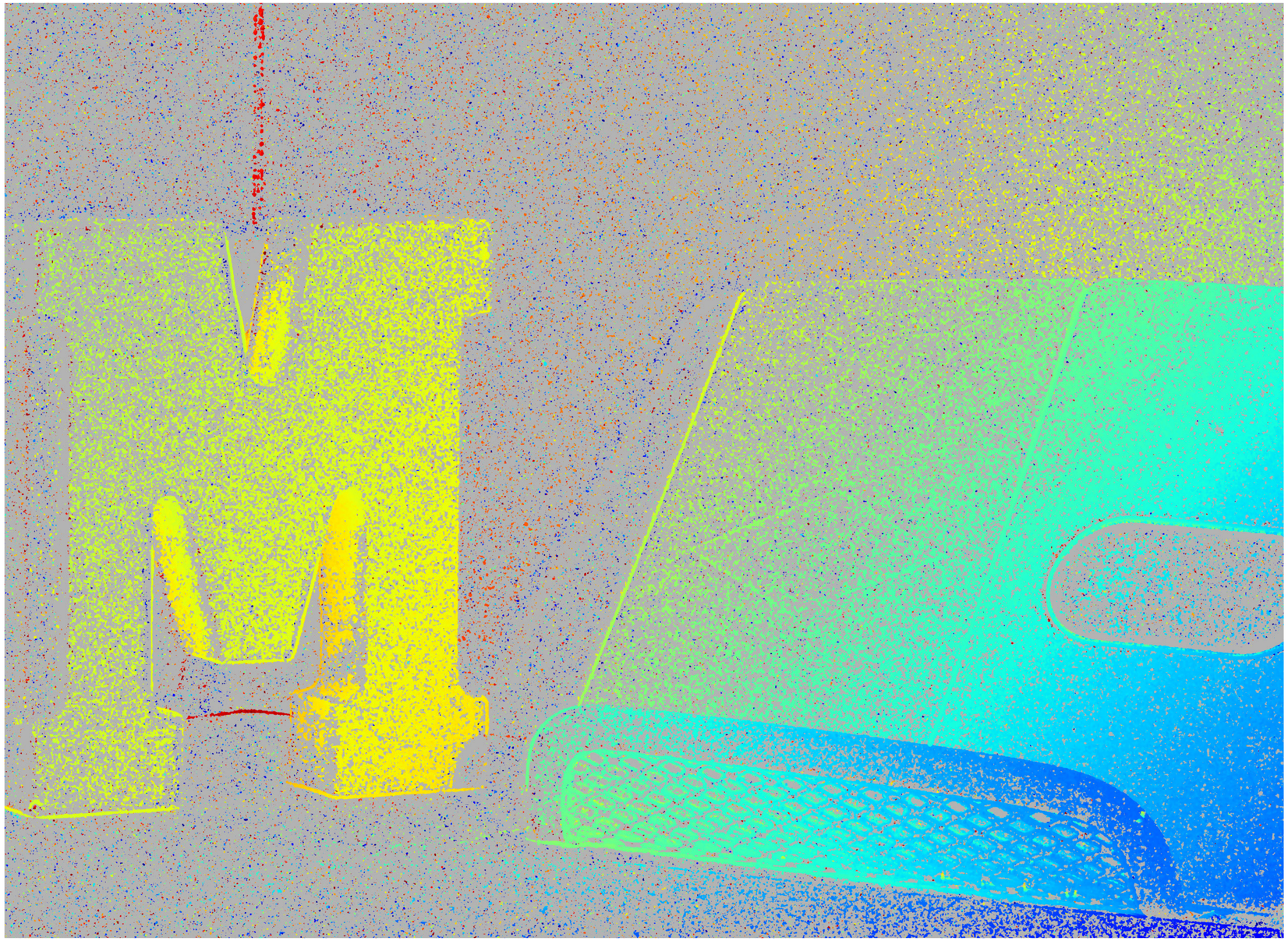
in-focus



defocused



the texture-SNR tradeoff

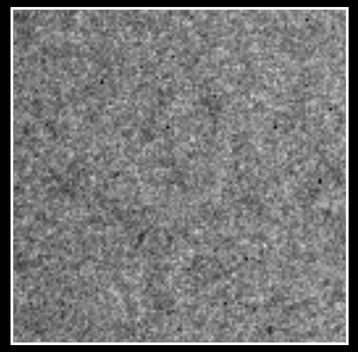


10 nm filter

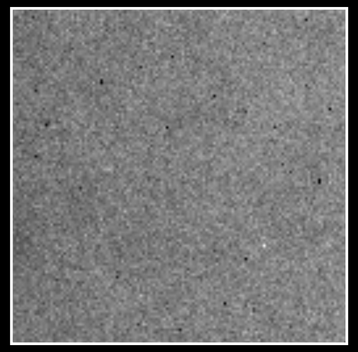
1/4x *underexposed*

8x exposure time

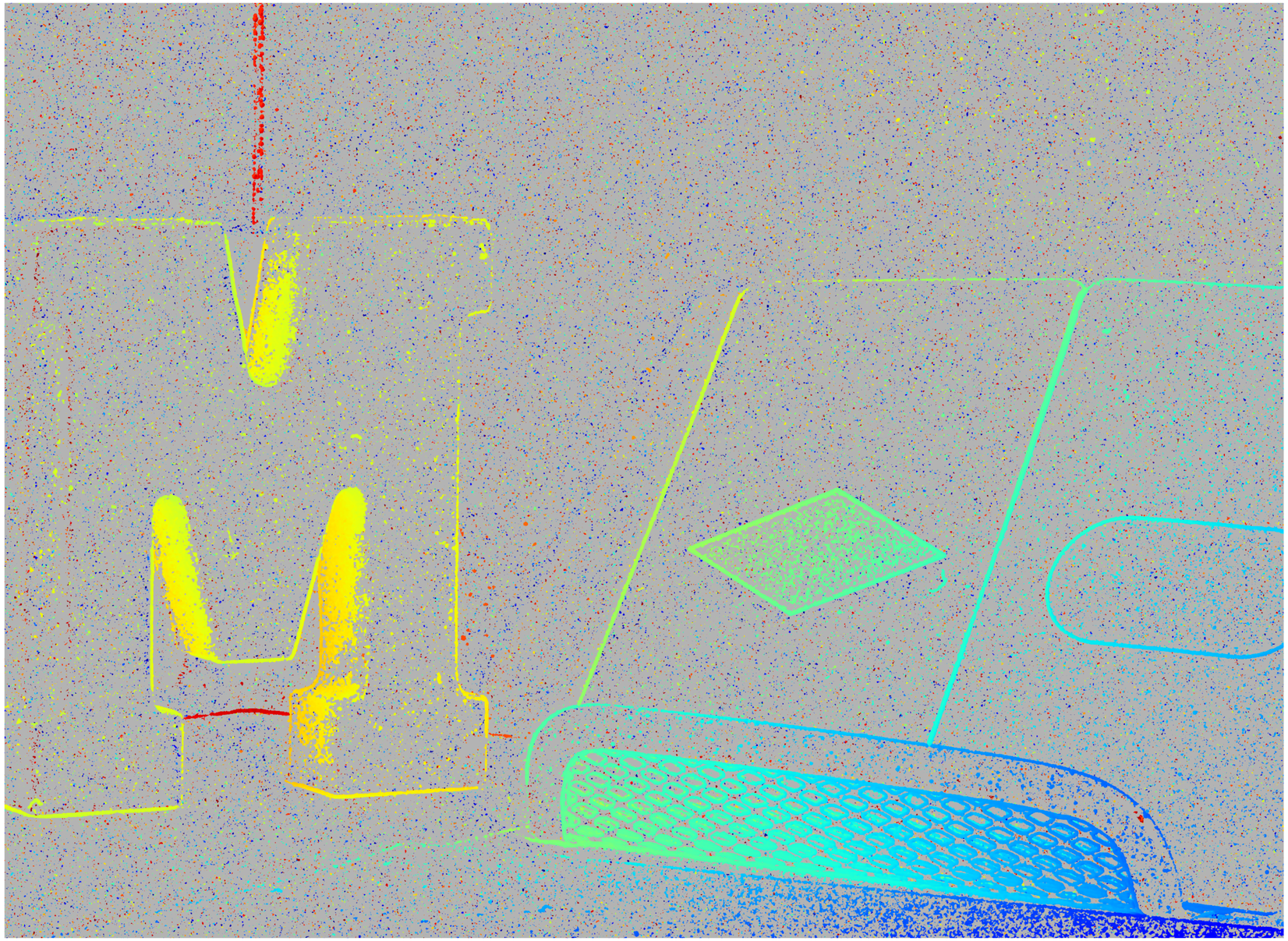
in-focus



defocused



the texture-SNR tradeoff

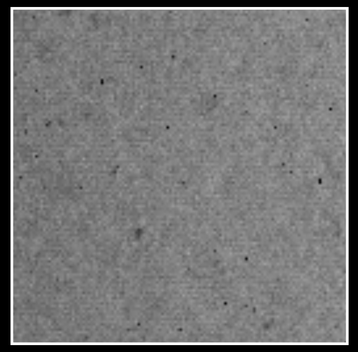


no filter

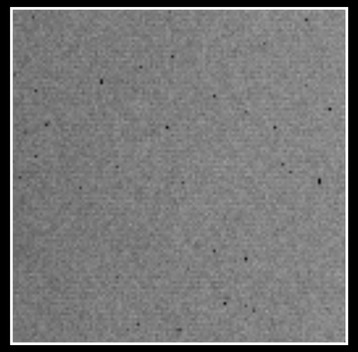
properly exposed

1x exposure time

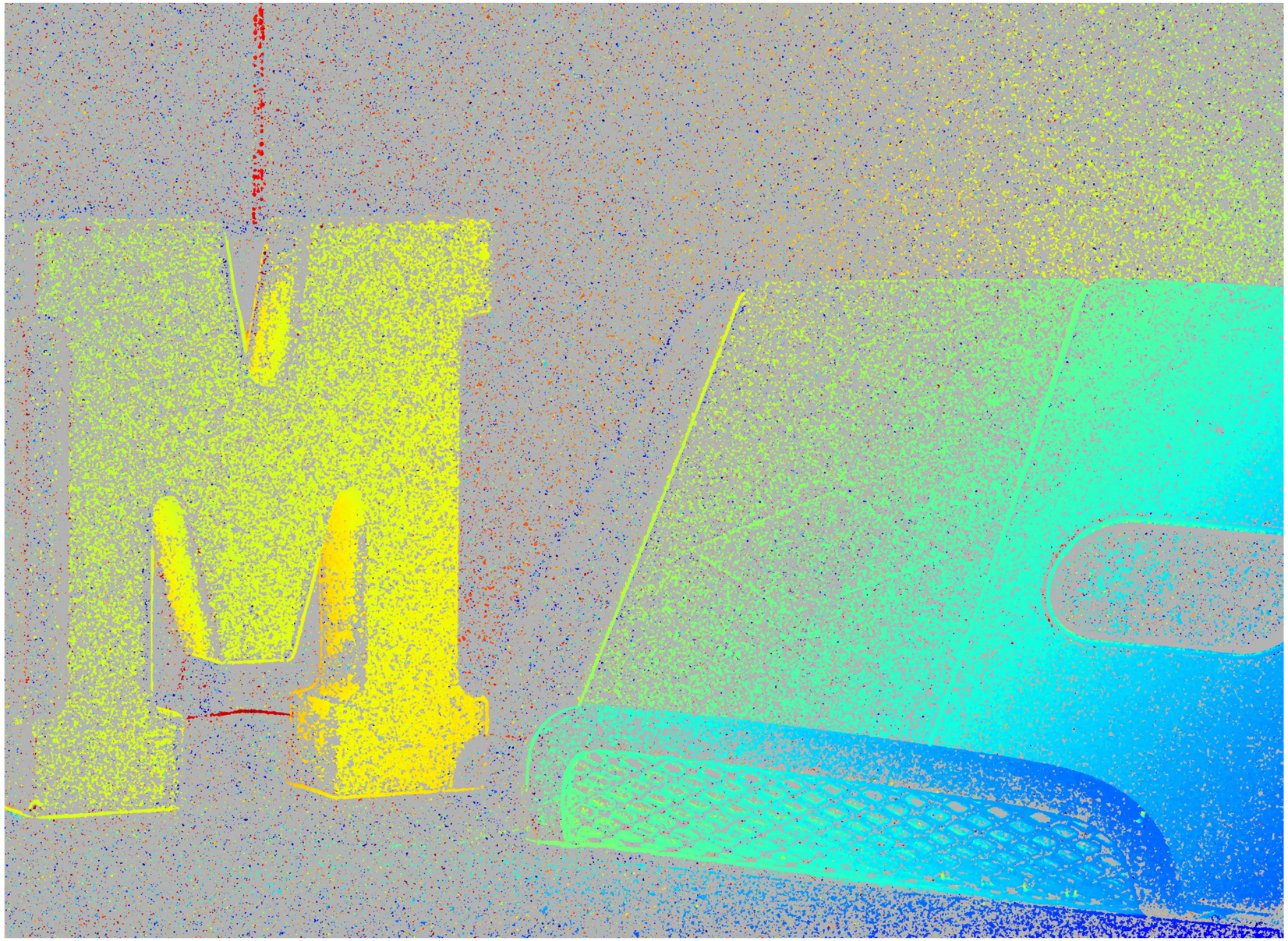
in-focus



defocused



the texture-SNR tradeoff

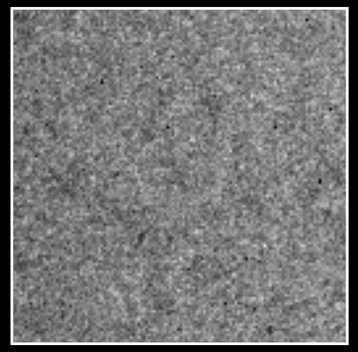


10 nm filter

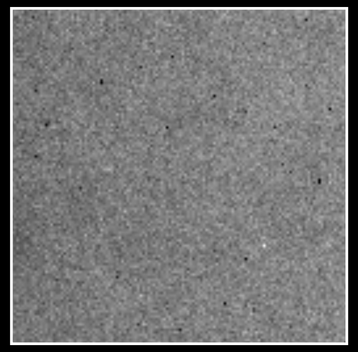
1/4x *underexposed*

8x exposure time

in-focus



defocused



Definition 8: Coherence Function

We define the *coherence function* $\Lambda_{\mathrm{i}}(\cdot)$ of the illumination environment map $\mathrm{L}_{\mathrm{i}}(\cdot)$ as its projected Fourier transform:

$$\Lambda_{\mathrm{i}}(\vec{\rho};k) := \int \mathrm{L}_{\mathrm{i}}(\hat{\omega})(\hat{\omega}\cdot\hat{n})e^{\mathrm{j}k\hat{\omega}_{xy}\cdot\vec{\rho}}\,\mathrm{d}\sigma(\hat{\omega})$$

Definition 3: Sample BRDF

Given a local surface heightfield $\mathrm{h}(\cdot)$, we define the *sample bi flectance distribution function* (sample BRDF) $\mathrm{f}_{\mathrm{r}}^{\mathrm{h}}$ as:

$$\mathrm{f}_{\mathrm{r}}^{\mathrm{h}}(\vec{q},\vec{u},k) := \frac{1}{A}\int_{\mathbb{R}^2} S(\vec{q},\vec{r},k,u_z)e^{\mathrm{j}k\vec{u}_{xy}\cdot 2}$$

Proposition 4: Appearance model

The irradiance received at sensor point $\vec{p}$ equals:

$$\mathrm{E}(\vec{p}) \approx \int\int \mathrm{w}_{\ell}(k)\ell(k)\mathrm{P}_{\mathrm{c}}(\vec{p}-\vec{q})\mathrm{L}_{\mathrm{o}}(\vec{q},\hat{v},k)\,\mathrm{d}\vec{q}\,\mathrm{d}k \quad \text{wher}$$

outgoing

Proposition 10: Model for second-order texture

The irradiance at point $\vec{p}$ can be approximately modelec

$$\mathrm{E}(\vec{p}) \approx \sum_m \Delta_{\mathrm{i}}^2\mathrm{P}_{\mathrm{c}}(\vec{p}-\vec{q}_m)\mathcal{L}^{(\Delta_{\mathrm{i}})}(\vec{q}_m$$

where the (blurred) outgoing radiance at grid locations $\vec{q}_m$ wi can be modeled as Gamma-distributed random variables

$$\mathcal{L}^{(\Delta_{\mathrm{i}})}(\vec{q}_m) \mid \overline{\mathcal{L}}^{(\Delta_{\mathrm{i}})}(\vec{q}_m) \sim \mathrm{Gamma}\left(M, \frac{M}{\overline{\mathcal{L}}^{(\Delta_{\mathrm{i}})}(\vec{q}_m)}\right)$$

Proposition 2: Necessary and sufficient condition for α-recoverability

For any $\alpha \in [0,1]$, the in-focus index j_{if} is α-recoverable if and only if:

$$\mathcal{Z}\left(\underbrace{\kappa_{\mathrm{I}}^2}_{\text{texture}} \cdot \underbrace{\frac{1}{\kappa_n^2}}_{\text{SNR}}\right) \cdot \underbrace{\sqrt{\frac{T-1}{2}}}_{\text{patch size}} > \Phi^{-1}(1-\alpha), \tag{3}$$

; and

Lemma 11: Marginal statistics of $\widetilde{\mathrm{C}}^2$

$$\mathbb{E}\left[\widetilde{\mathrm{C}}^2\right] = \frac{\sigma_{\widetilde{\mathrm{I}}}^2}{\mu_{\widetilde{\mathrm{I}}}^2} = \kappa_{\widetilde{\mathrm{I}}}^2 = \kappa_{\mathrm{I}}^2 + \kappa_n^2 \tag{146}$$

$$\mathbb{V}\left[\widetilde{\mathrm{C}}^2\right] = \frac{\left(\kappa_{\widetilde{\mathrm{I}}}^2\right)^2}{T}\left(\kappa_4 - \frac{T-3}{T-1}\right) \tag{147}$$

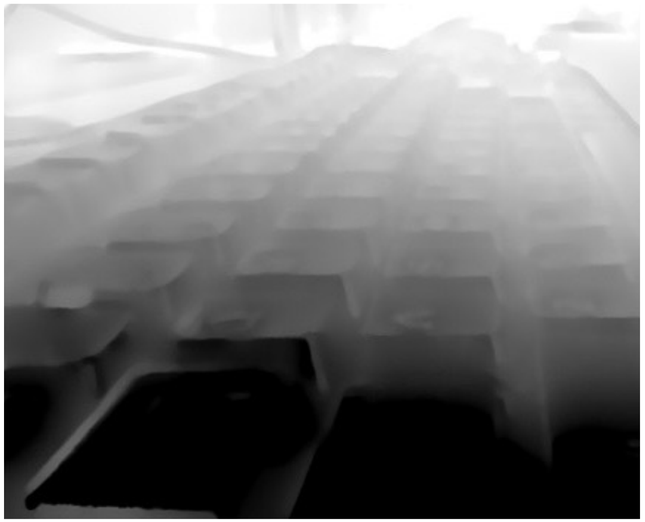
Proposition 7: Texture contrast–SNR product

In focus, the texture contrast–SNR product $\Theta^2 := \kappa_{\mathrm{I}}^2/\kappa_n^2$ equals:

$$\Theta^2(t,\Delta_k) \approx \frac{1}{Q}\frac{G_2}{G_1}\frac{t}{\left(1+\frac{\sigma_{\mathrm{read}}^2}{G_2}\frac{1}{\Delta_k t}\right)}, \tag{12}$$

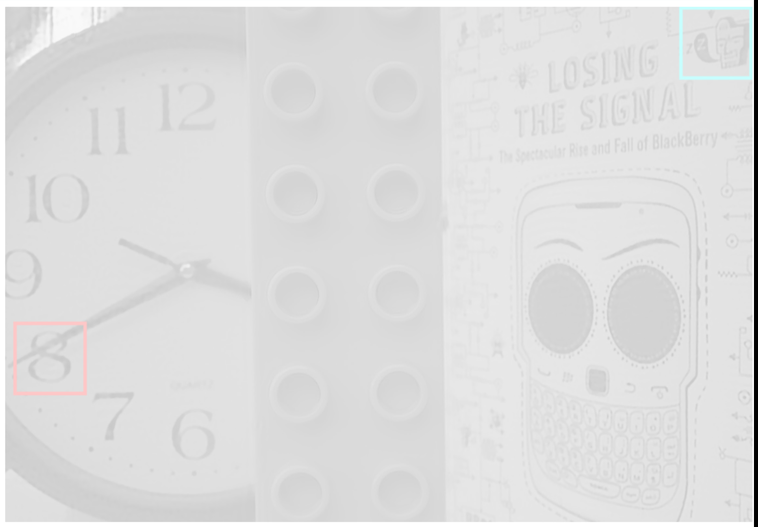
where the exposure time $t \in [0, g\mathrm{I}_{\max}/G_2\Delta_k)$ has a saturation limit dependent on spectral bandwidth Δ_k, and the constant G_2 depends on spectral reflectance.

depth from focus



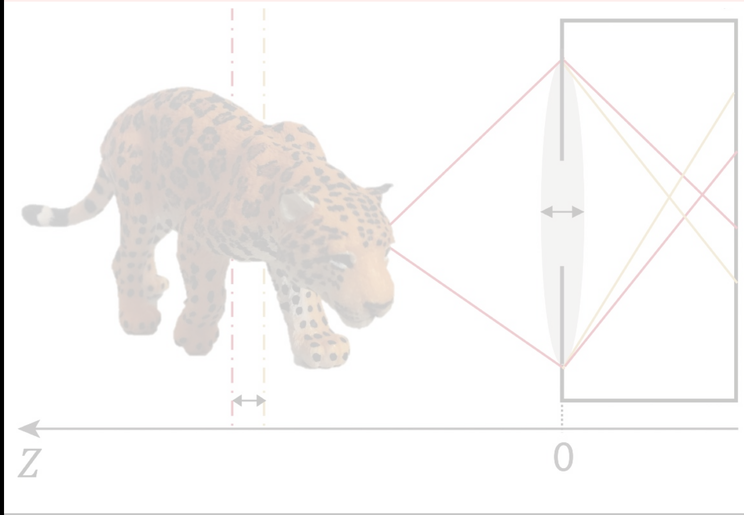
Suwajanakorn et al. 2015 Hasinoff & Kutulakos 2006

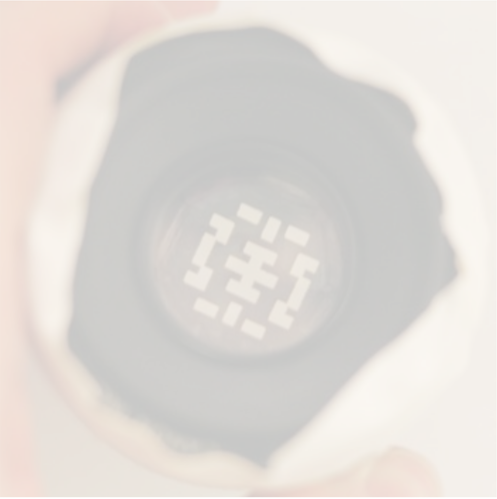
light fields / dual pixel



Ng. et al. 2005 Xin et al 2021

depth from defocus



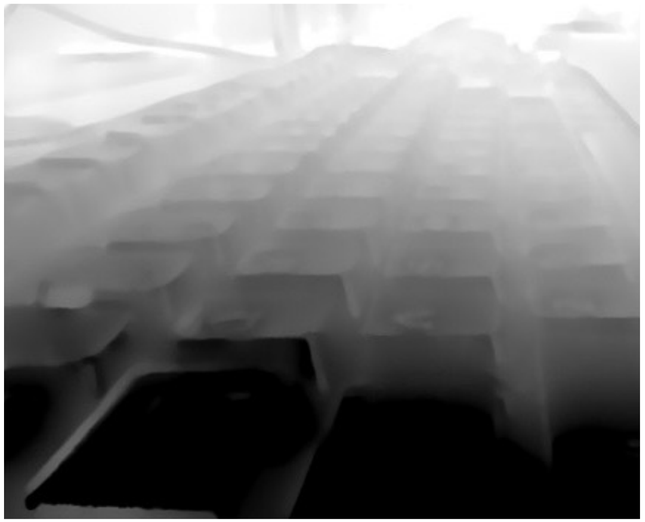


Guo et al. 2017 Levin et al. 2007

multi-view stereo

Scharstein & Szeliski 2002

depth from focus



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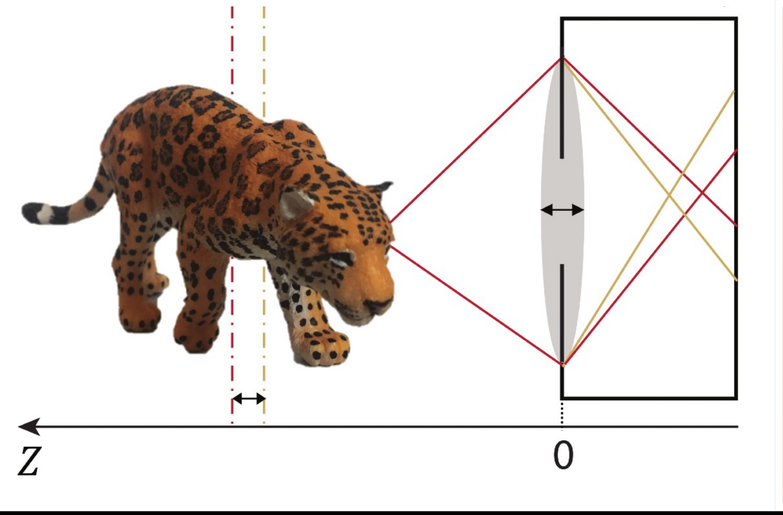

Guo et al. 2017 Levin et al. 2007

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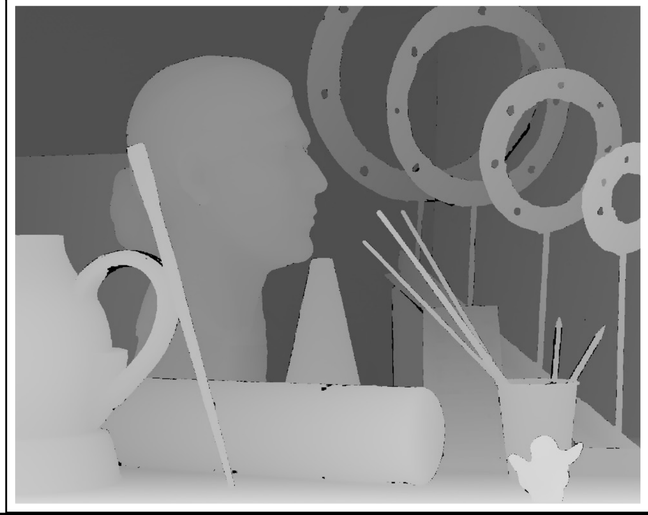
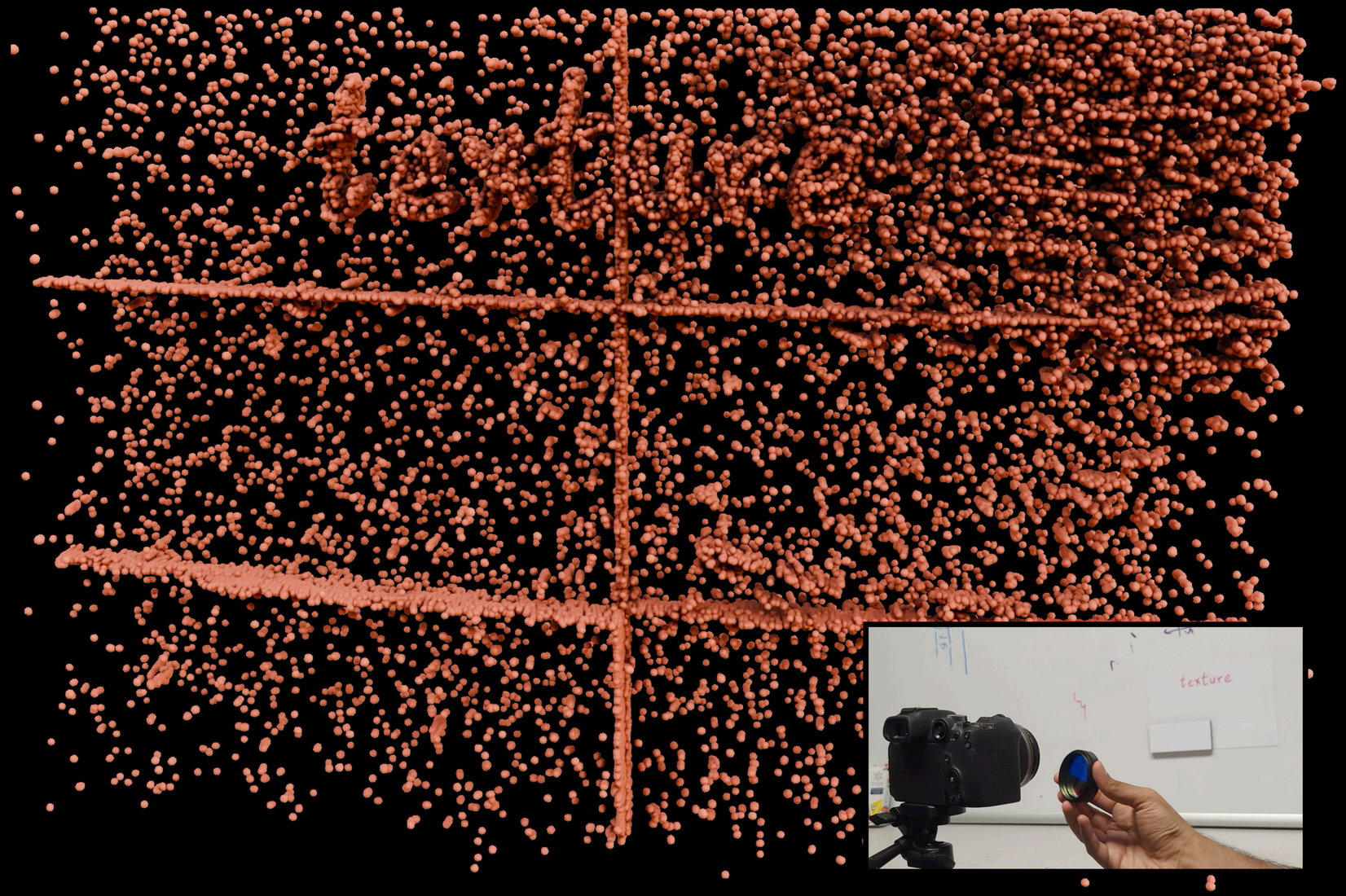


Scharstein & Szeliski 2002

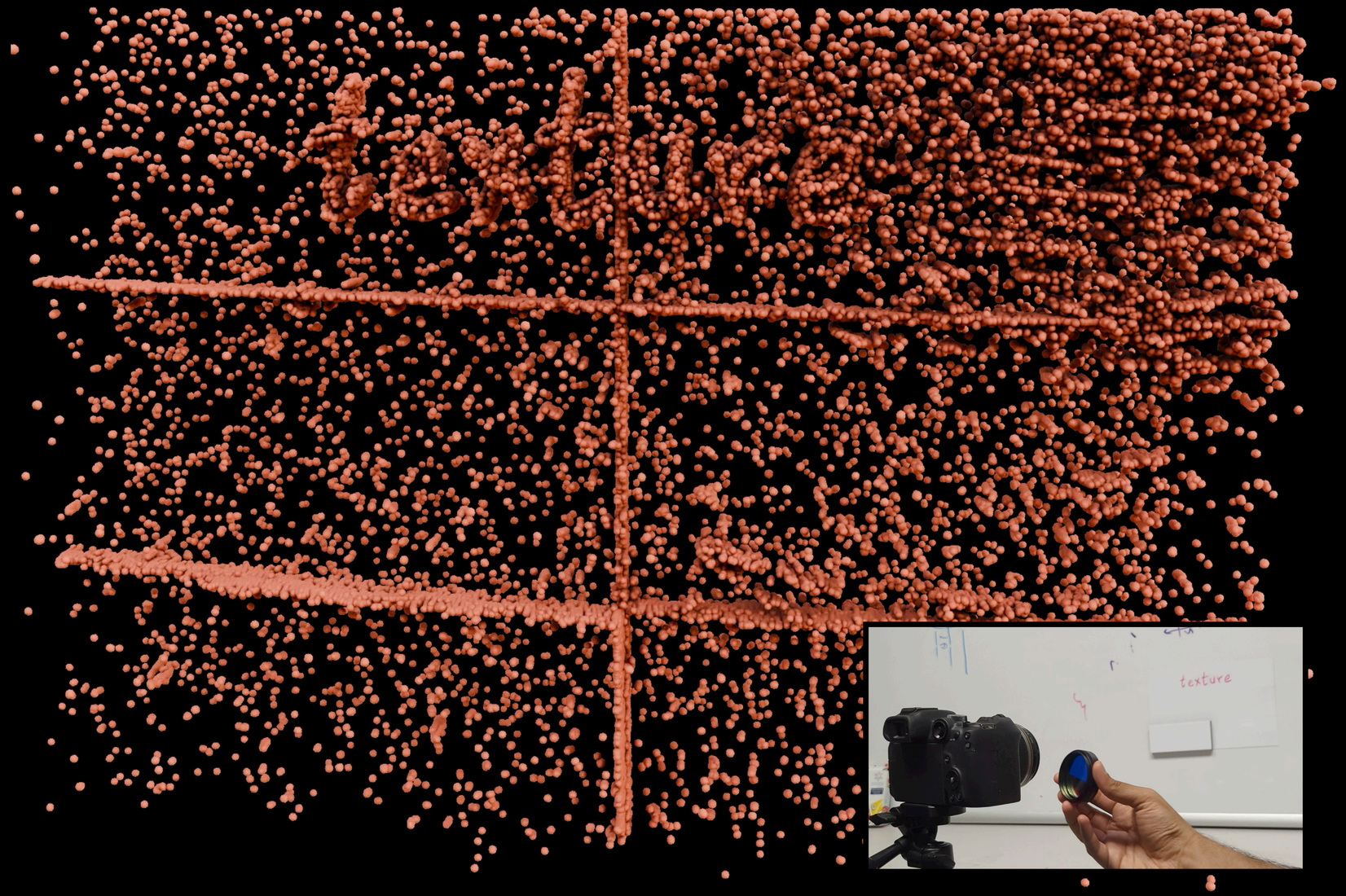
project website with interactive visuals, additional results, and more.



project page: https://imaging.cs.cmu.edu/second-order-texture

Visit us: **Poster # 50** today and **demo** on Saturday morning.

project website with interactive visuals, additional results, and more.



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end