Carnegie Mellon University

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Depth and Matte Recovery for Multilayer Thin Structures

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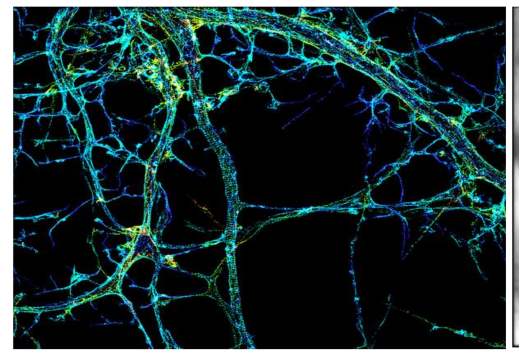
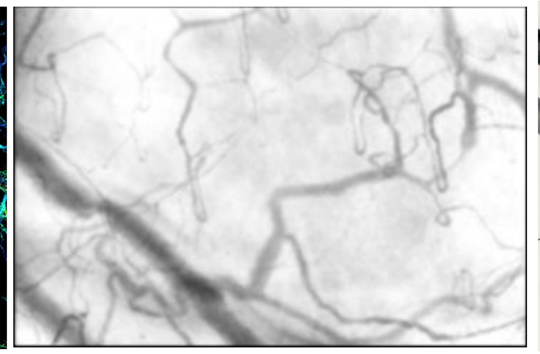
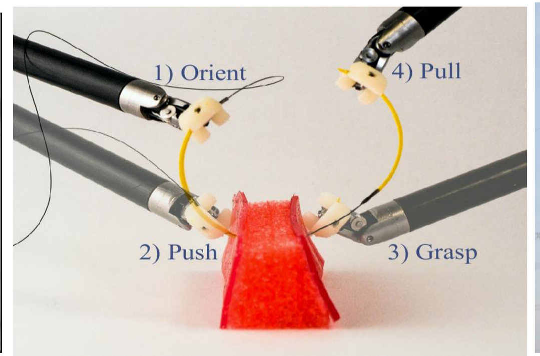
Motivation: thin structures are common


Neural Science


Vascular Study



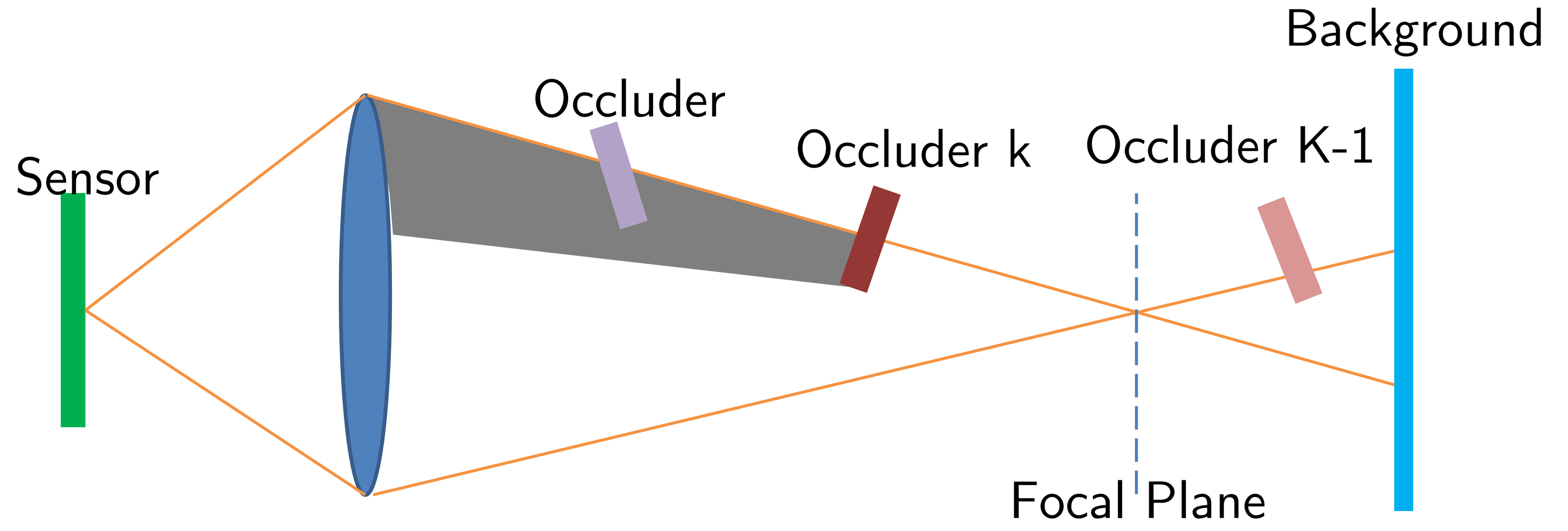
Robotic Assisted Surgery


Drone Navigation

Challenges in estimating the depth for thin structures:

- Textureless: feature matching based method easily fail.
- Fine-grained structures: high spatial frequency in depth discontinuities.
- Mutual occlusions.

Multi-layer image formation model



$$R^m(\boldsymbol{x}) = \sum_k \underbrace{\alpha_k^m(\boldsymbol{x})}_{\text{occlusion}} \sum_{\boldsymbol{u}} \underbrace{M_k(\boldsymbol{u})}_{\text{matting}} \overbrace{L_k(\boldsymbol{u})}^{\text{radiance}} \overbrace{B_k^m(\boldsymbol{u}-\boldsymbol{x}, d)}^{\text{blur}}$$

$$\alpha_k^m(\boldsymbol{x}) = \begin{cases} 1 \\ \prod_{1\le j\le k-1} 1 - \sum_{\boldsymbol{u}} M_j(\boldsymbol{u}) B_j^m(\boldsymbol{u}-\boldsymbol{x}, d) \end{cases}$$

$M(\boldsymbol{x}) \in \{0,1\}$: Occlusion matte, Boolean
$d(\boldsymbol{x}) \ge 0$: Depth, Continuous
$L(\boldsymbol{x}) \ge 0$: Radiance, Continuous

$M_1(\boldsymbol{x}) = 1$
$R^m(\boldsymbol{x}) = R(occ) + \alpha R(bkg)$

$M_1(\boldsymbol{x}) = 0$
$R^m(\boldsymbol{x}) = R(bkg)$

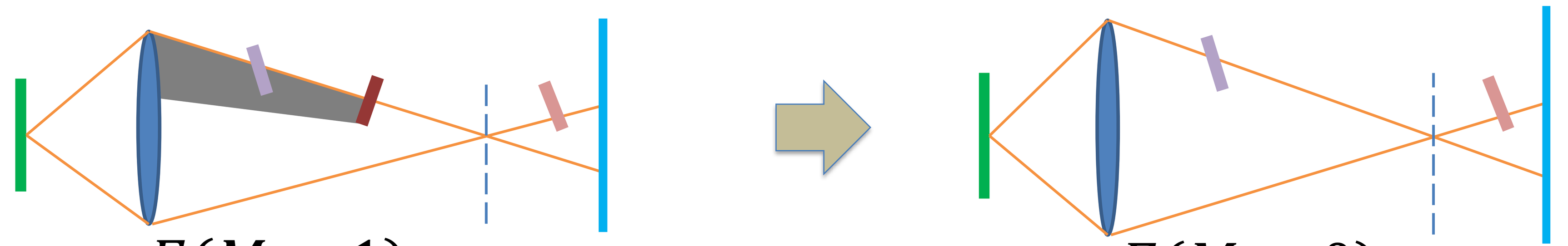
Unknowns for image size WxH: 2KWH continuous and KWH boolean

Multi-layer Matting and Depth Estimation

Boolean optimization for $M \in \{0,1\}$: Gradient of MCMC

Problem Formation: Given focal stack images $\{R_m\}$ Estimate $\{M, d\}$

$$\min_{M,d} \underbrace{\Big(I(\boldsymbol{x}) - R\big(\boldsymbol{x}; M(\boldsymbol{x}), d(\boldsymbol{x})\big)\Big)^2}_{\text{Scene Model}} + \underbrace{S_m(M) + S_d(d)}_{\text{Regulizers}}$$



$E(M=1)$ $E(M=0)$

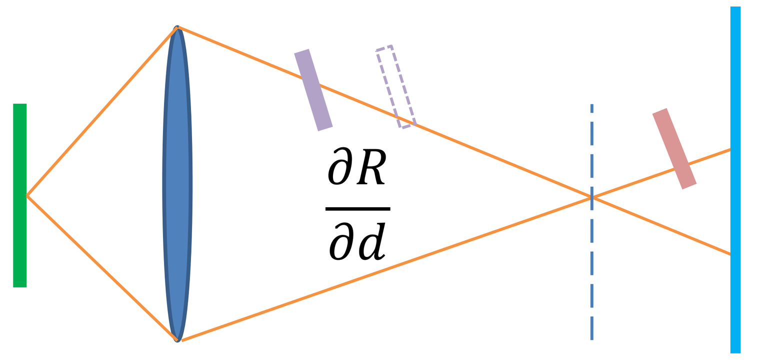
Need to get $\Delta E = E(M=1) - E(M=0)$ for MCMC.
Slow, need to re-render the image per-sampling per-pixel.

Compute:

$$\Delta E = \sum_x \Delta R(\boldsymbol{x})(\Delta R(\boldsymbol{x}) + 2(R(\boldsymbol{x}) - I(\boldsymbol{x}))) + \Delta S_m$$

Differential radiance $\Delta R(\boldsymbol{x})$. Fast to compute analytically.

Continuous optimization for $d \in R$: Gradient Descent

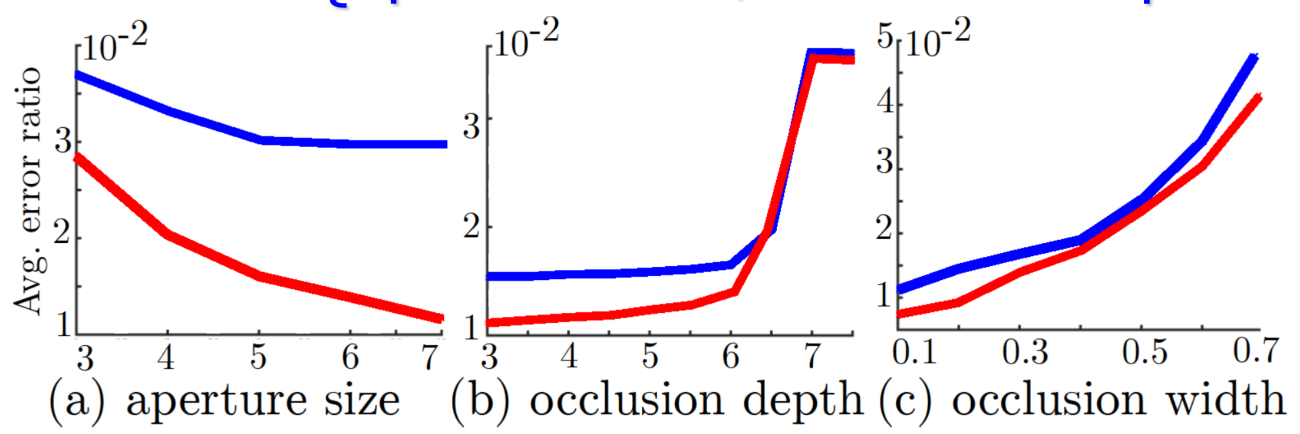


Chain rule:

$$\frac{\partial E}{\partial d} = \frac{\partial E}{\partial R}\frac{\partial R}{\partial d}$$

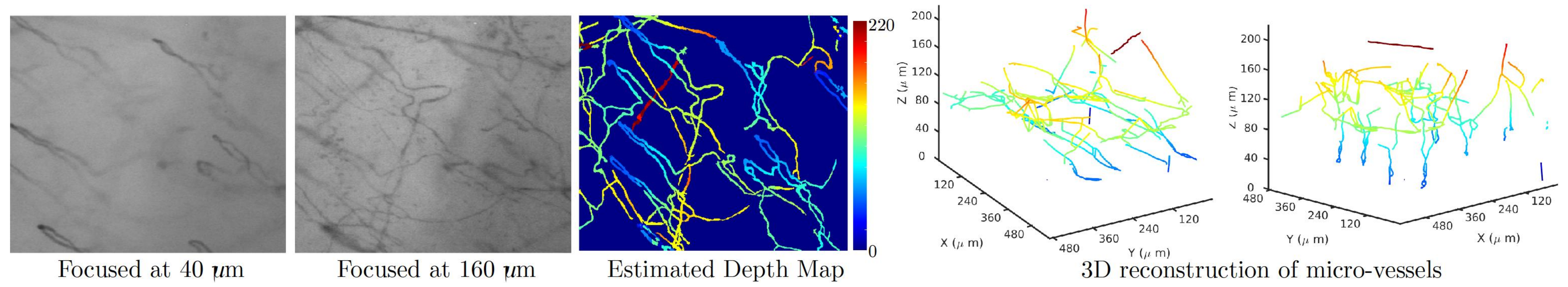
$\frac{\partial R}{\partial d}$ computed analytically.

Performance vs. {aperture size, occlusion depth & width}

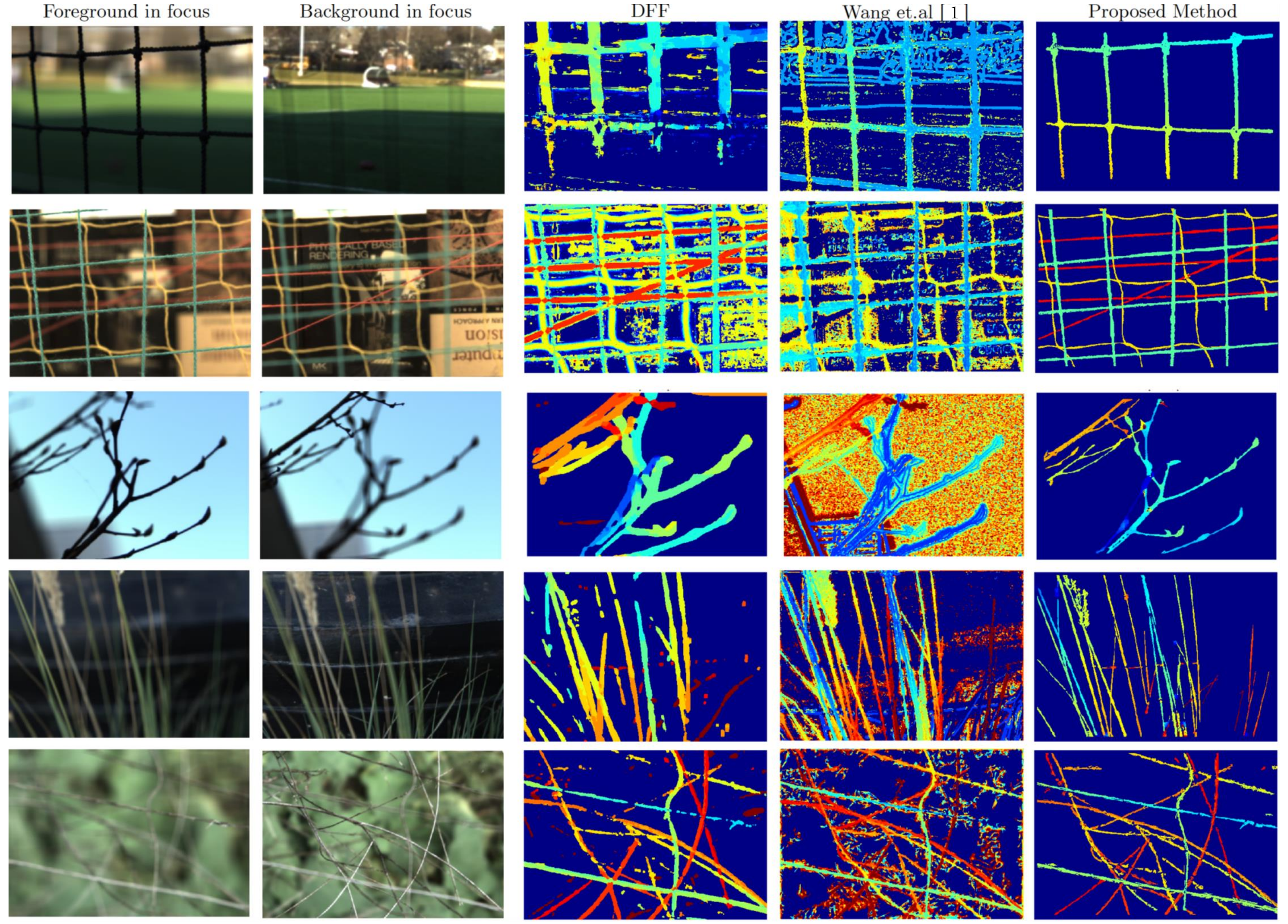


Results

Scene in micro-scale



Scenes in conventional scale



Reference:

[1] *T.C Wang et.al.* Occlusion-aware Depth Estimation Using Light-field Cameras. ICCV 2015
[2] *A. Levin et.al.* A closed form solution to natural image matting. CVPR 2006
[3] *J.Gu et.al.* Removing image artifacts due to dirty camera lenses and thin occluders. TOG 2009