I can see clearly now: Sub-diffraction limit 3D coherent lidar imaging

TONY ALLEN
AFRL/RYMM
Purdue University

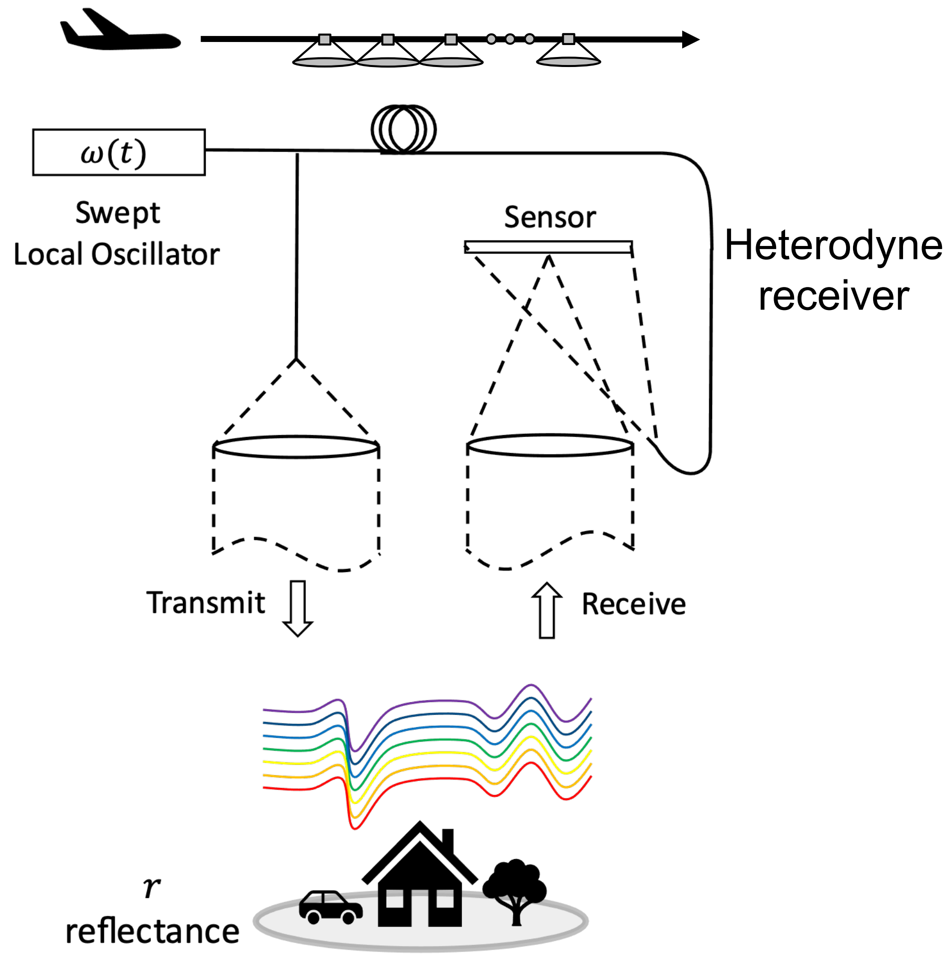
Dr. David Rabb – AFRL/RYMM
Dr. Gregery Buzzard – Purdue University
Dr. Charles Bouman – Purdue University

INTEGRATED IMAGING

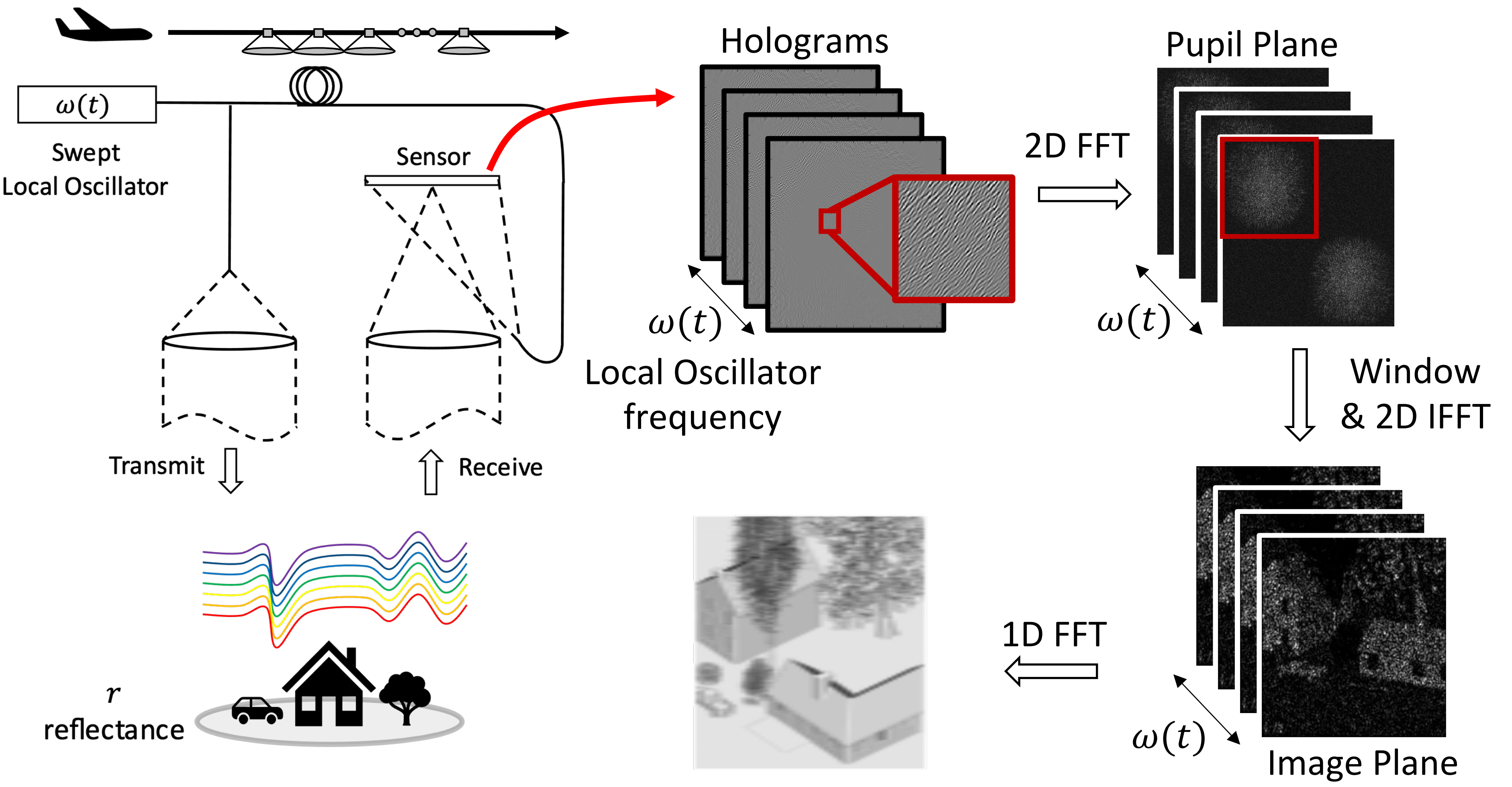
AFRL
THE AIR FORCE RESEARCH LABORATORY

3D Coherent LIDAR Imaging

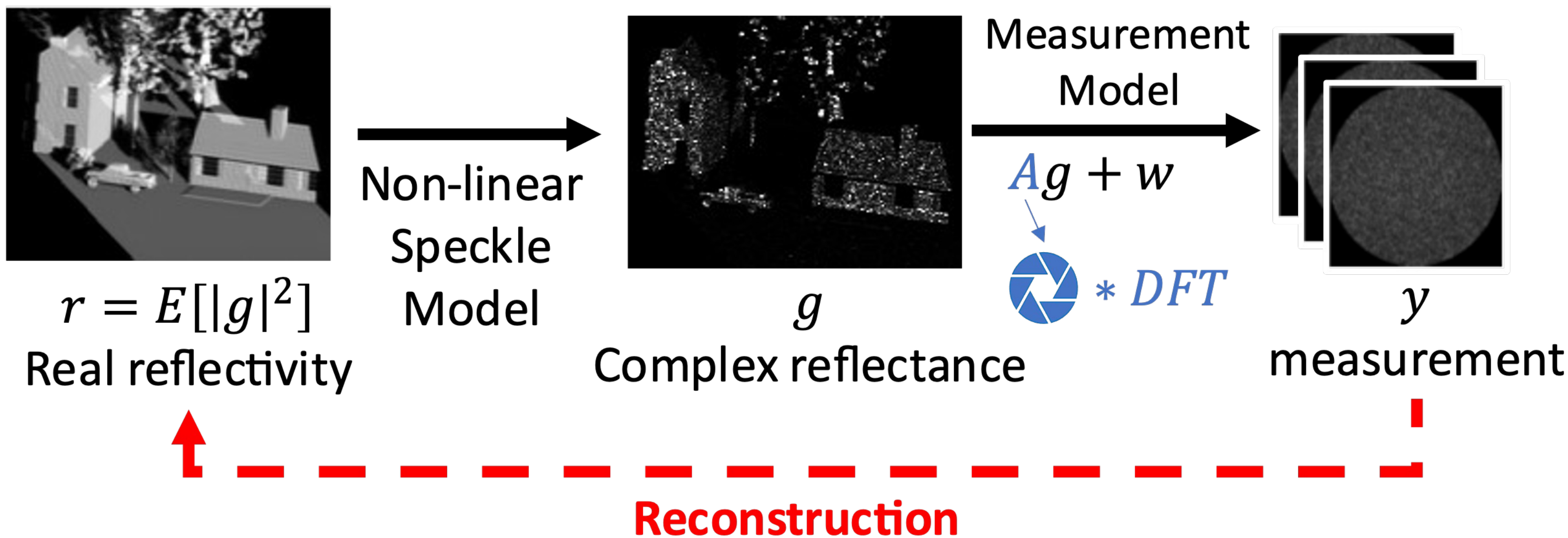
- **Goal:** Long-range 3D imaging
- **Strategy:**
  - Heterodyne detection to capture complex image
  - Sweep local oscillator frequency to obtain depth



Conventional LIDAR Processing



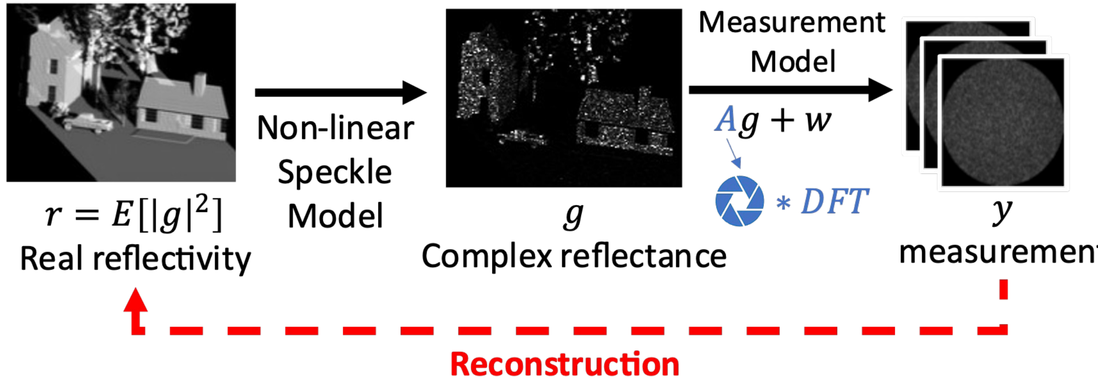
LIDAR Forward Model



- MBIR Approach

$$\hat{r} = \arg\min_{r}\{-\log p(y|r) - \log p(r)\}$$

Exact Update for MBIR*



E-Step

Estimate statistics of g

$$C \leftarrow \left(A^H A + \mathrm{diag}(\sigma_w^2 / r)\right)^{-1}$$

$$\mu \leftarrow C A^H y$$

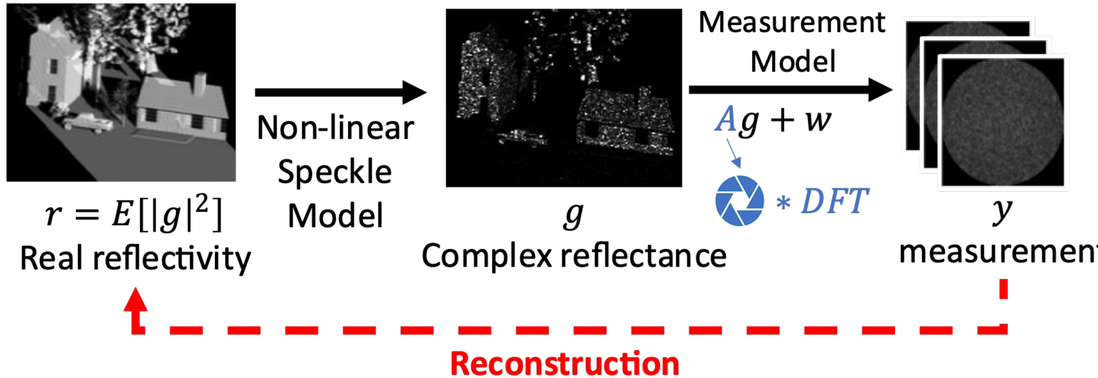
M-Step

Use μ, C to estimate r

$$r \leftarrow \arg\min_r \left\{ \sum_i \left\{ \log r_i + \frac{|\mu_i|^2 + C_{i,i}}{r_i} \right\} - \log p(r) \right\}$$

*C.J. Pellizzari et al., "Phase-error estimation and image reconstruction from digital-holography data using a Bayesian framework", J. Opt. Soc. Am., 2017

Exact Update for MBIR*



intractable

E-Step

Estimate statistics of g

$$C \leftarrow \left(A^H A + \mathrm{diag}(\sigma_w^2 / r)\right)^{-1}$$
$$\mu \leftarrow C A^H y$$

M-Step

Use μ, C to estimate r

$$r \leftarrow \arg\min_r \left\{ \sum_i \left\{ \log r_i + \frac{|\mu_i|^2 + C_{i,i}}{r_i} \right\} - \log p(r) \right\}$$

*C.J. Pellizzari et al., "Phase-error estimation and image reconstruction from digital-holography data using a Bayesian framework", J. Opt. Soc. Am., 2017

Approximate Update for MBIR*

- Pellizzari: Assume that $A^H A = I$, so…

E-Step

$$C \leftarrow \left(I + \mathrm{diag}(\sigma_w^2 / r)\right)^{-1}$$

$$\mu \leftarrow C A^H y$$

M-Step

$$r \leftarrow \arg\min_r \left\{ \sum_i \left\{ \log r_i + \frac{|\mu_i|^2 + C_{i,i}}{r_i} \right\} - \log p(r) \right\}$$

- Advantage: Easy to compute
- Disadvantages:
  - Ignores aperture blur 
  - Propagates error to μ

*C.J. Pellizzari et al., "Phase-error estimation and image reconstruction from digital-holography data using a Bayesian framework", J. Opt. Soc. Am., 2017

Our Update for MBIR

- Our Approach: Approximate C, but find μ exactly

E-Step

$$C \leftarrow \left(I + \mathrm{diag}(\sigma_w^2/r)\right)^{-1}$$

$$\boldsymbol{\mu} \leftarrow \arg\min_{g} \left\{ \frac{1}{\sigma_w^2} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{g}\|^2 + \|\boldsymbol{g}\|_{1/r}^2 \right\}$$

M-Step

$$r \leftarrow \arg\min_{r} \left\{ \sum_i \left\{ \log r_i + \frac{|\mu_i|^2 + C_{i,i}}{r_i} \right\} - \log p(r) \right\}$$

- **Advantages:**
  - **Accounts for aperture blur**
  - **Error in C doesn't propagate to μ**

Our Update for MBIR

- Our Approach: Approximate C, but find μ exactly

E-Step

$$C \leftarrow \left(I + \mathrm{diag}(\sigma_w^2/r)\right)^{-1}$$

$$\boldsymbol{\mu} \leftarrow \boldsymbol{\mu} - \boldsymbol{\alpha}\nabla \boldsymbol{f}(\boldsymbol{\mu})$$

where $\boldsymbol{f}(\boldsymbol{g}) = \frac{1}{\sigma_w^2}\|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{g}\|^2 + \|\boldsymbol{g}\|_{1/r}^2$

M-Step

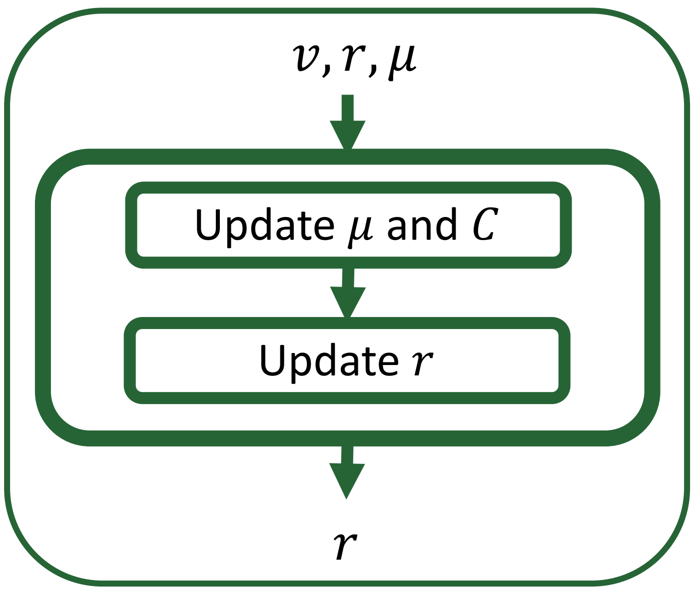
$$r \leftarrow \arg\min_r \left\{ \sum_i \left\{ \log r_i + \frac{|\mu_i|^2 + C_{i,i}}{r_i} \right\} - \log p(r) \right\}$$

- **Advantages:**
  - **Accounts for aperture blur**
  - **Error in C doesn't propagate to μ**
  - **Easy to compute**

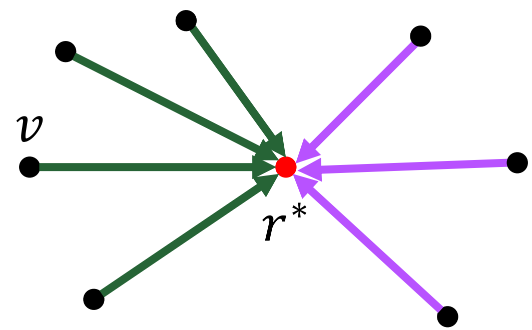
3D-MACE: LIDAR Reconstruction Algorithm

- 3D-Multi Agent Consensus Equilibrium (**3D-MACE**)
  - Solution balances **Forward Agents** and **Prior Agents**

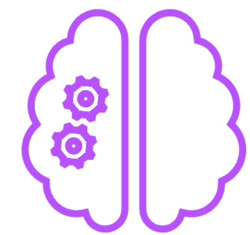
Forward Agents



- Integrate multi-look data as individual agents



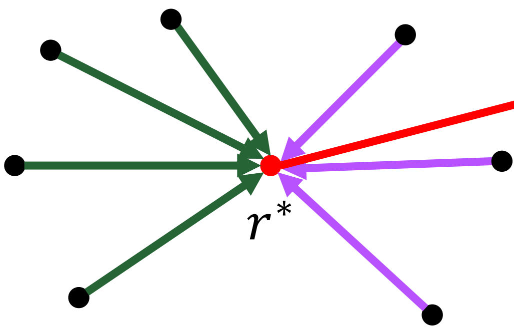
Prior Agents



- CNNs trained on natural images
- Applied to 2D slices of 3D image

3D-MACE: LIDAR Reconstruction Algorithm

- 3D-Multi Agent Consensus Equilibrium (**3D-MACE**)
  - Solution balances **Forward Agents** and **Prior Agents**



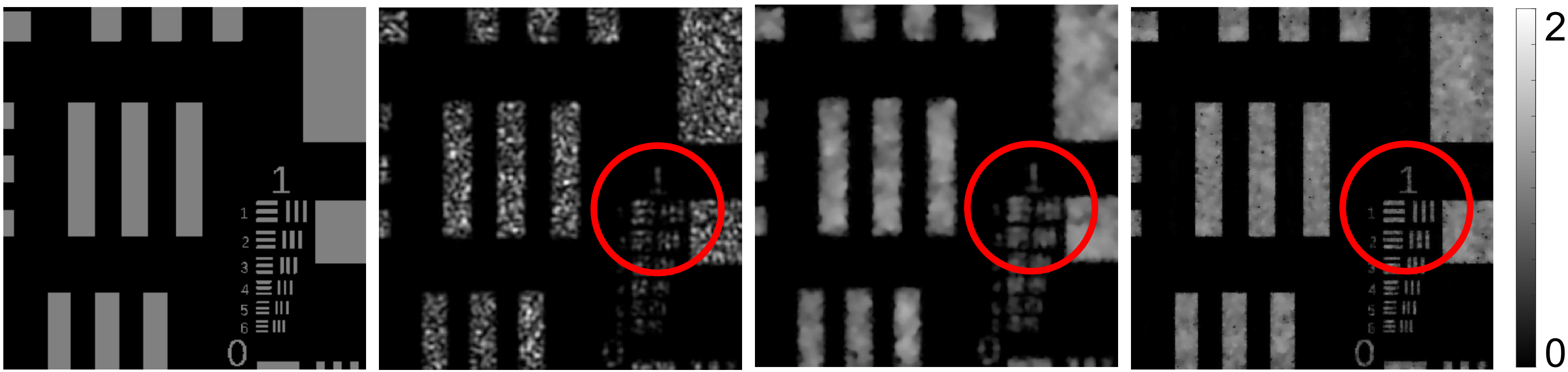
  - Solved by iterative fixed-point algorithm*
    - $r \leftarrow (1-\rho)r + \rho(2G - I)(2F - I)r$

*G. T. Buzzard et al., "Plug and play unplugged: Optimization Free Reconstruction using Consensus Equilibrium", SIAM J. Imaging Science., 2017

Results – Simulated 2D Bar Chart

Reconstructions with 4 looks

Ground Truth



Traditional Reconstruction

$$\hat{r} = \frac{1}{4}\sum_{\ell} |A^H y_\ell|^2$$

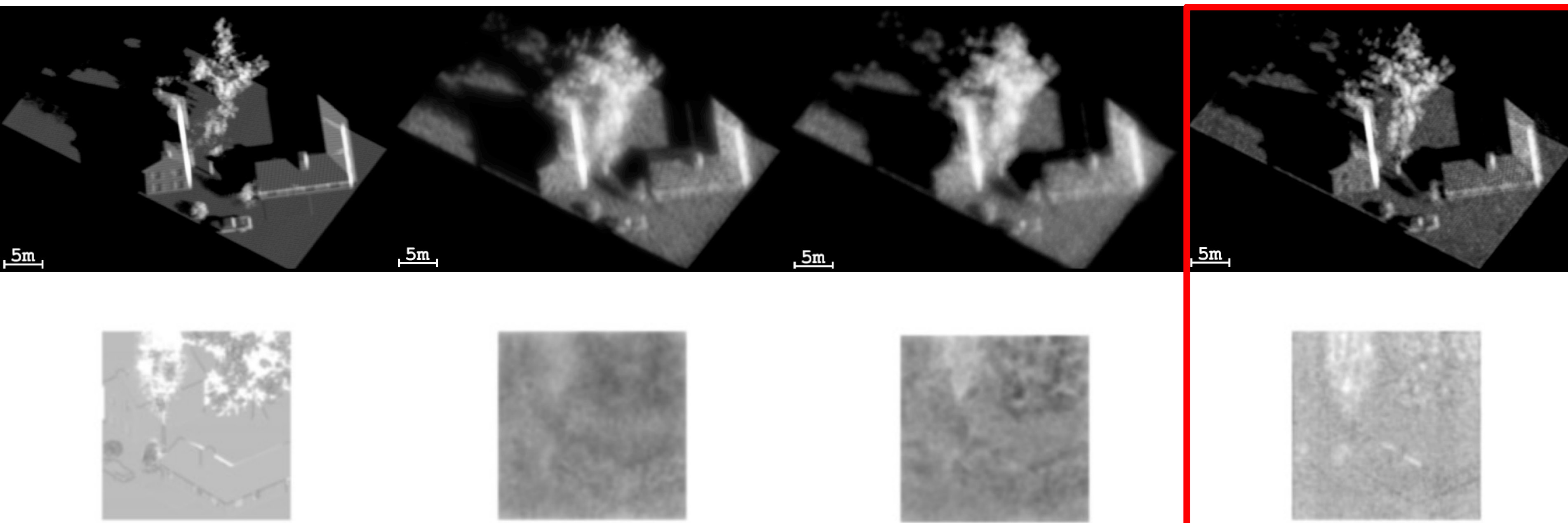
MACE Solution (No aperture model)

MACE Solution (With aperture model)

Results – Simulated 3D Scene

Reconstructions with 8 looks

Ground Truth



Traditional Reconstruction

$$\hat{r} = \frac{1}{8}\sum_{\ell} |A^H y_\ell|^2$$

3D-MACE Solution (No aperture model)

3D-MACE Solution (with aperture model)

Takeaways

- 3D-MACE Algorithm
  - Fast EM-updates for removing aperture blur
  - Represent each look by an EM-Agent
  - Prior model is implemented with CNN
- Results:
  - Speckle-reduced images
  - Resolution beyond diffraction limited resolutions

Thank You

Contact: allen450@purdue.edu

TONY ALLEN