

Online 3D imaging in high-background scenarios

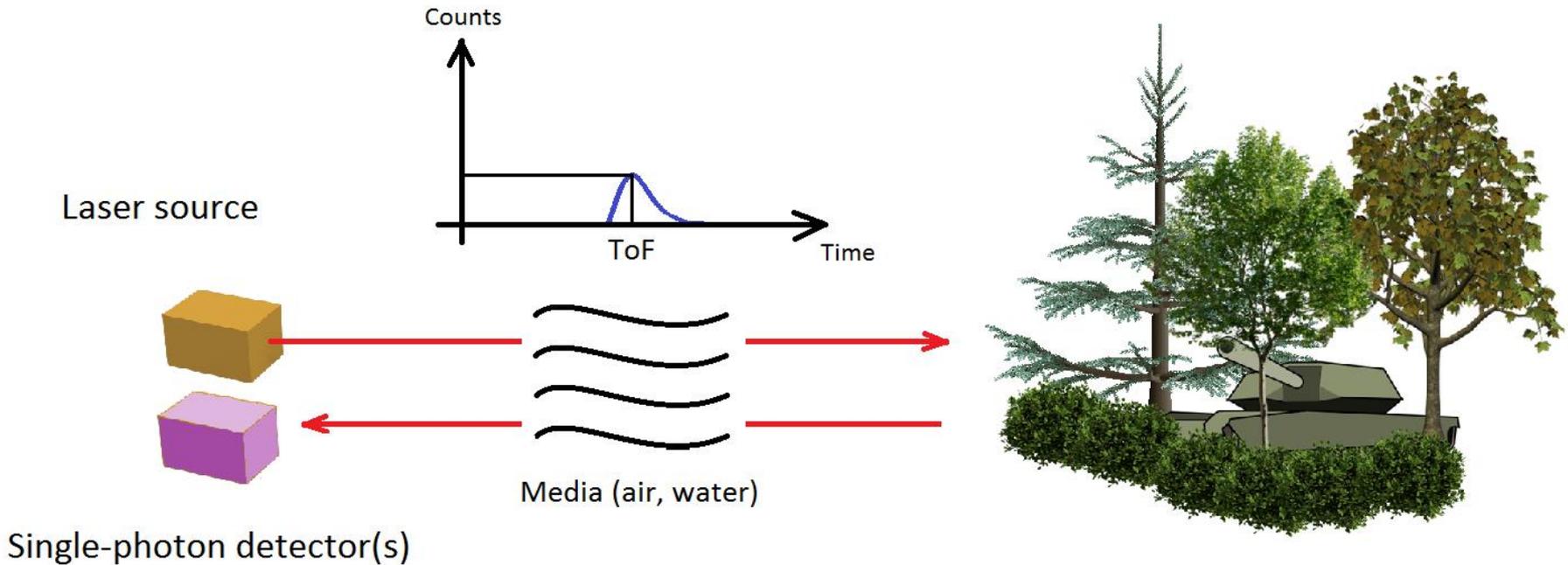
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Joint work with: Julian Tachella, Quentin Legros, Aurora Maccarone, Rachael Tobin, Aongus McCarthy, Gerald Buller, Stephen McLaughlin, Mike Davies

*UDRC Themed Meeting: Imaging through obscure media
July, 22nd 2020*

Single-photon Lidar

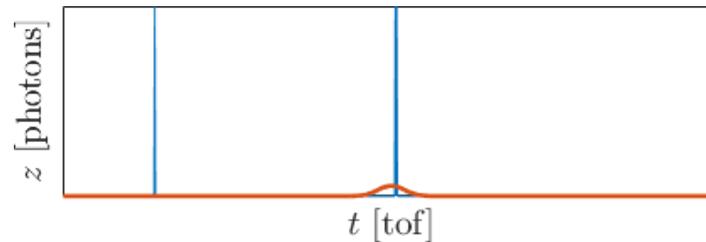


- Pulsed laser (20 MHz), low power ($\approx \mu\text{W}$)
- Detector(s): single-photon avalanche diode (SPAD)

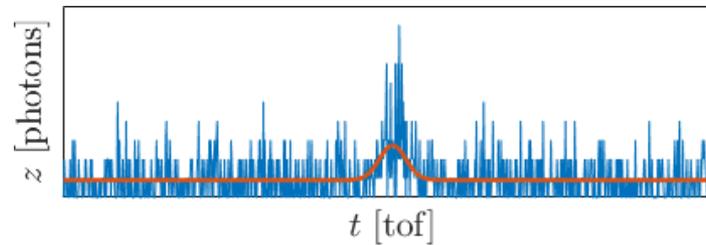
High sensitivity and high temporal/ranging resolution

Challenges (I)

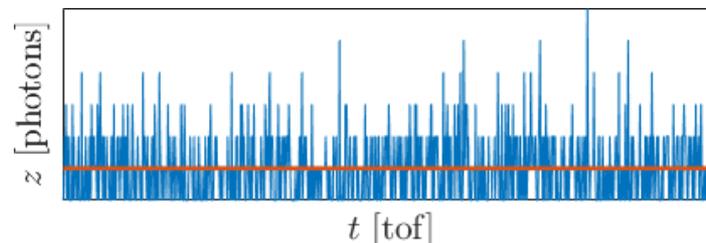
1. Few detected photons $s_t = r_0 g_0(t - t_0) \ll 1$



2. High background $b \gg s_t$



3. No target $s_t = 0$



Challenges (II)

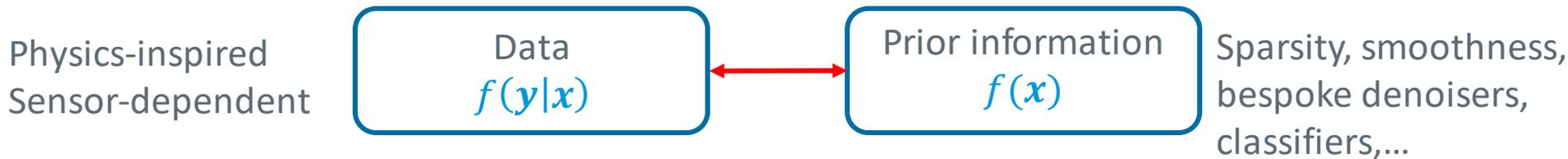
- Not only difficult inference problems (noise, convexity,...)
- Fast acquisition
- Large data volume/array size

- Optimization \neq fast
 - Dimensionality of the data/unknowns
 - Convergence speed

- Need to redesign the inference process
 - Scalability
 - Robustness

Algorithmic scalability

- Graph-based representation



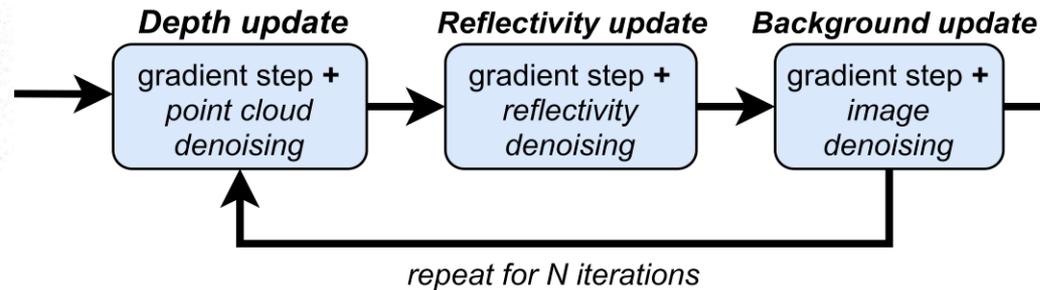
$$f(\mathbf{x}|\mathbf{y}) \propto f(\mathbf{y}|\mathbf{x})f(\mathbf{x})$$

- Message passing structure
- Plug-and-play (PnP): computer graphics

RT3D algorithm

raw Lidar data

3D reconstruction

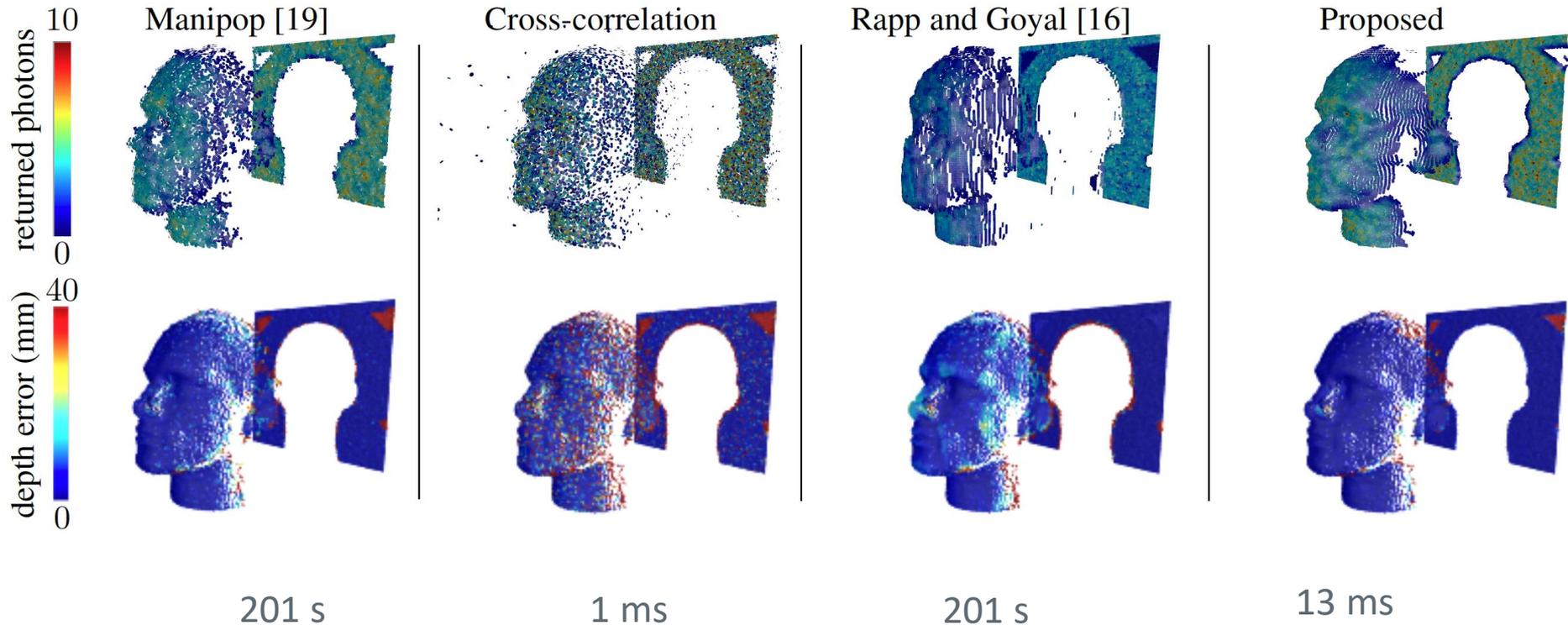


Significant gain using:

- Fast denoisers (e.g. parallel architectures)
- Application/variable-specific denoisers

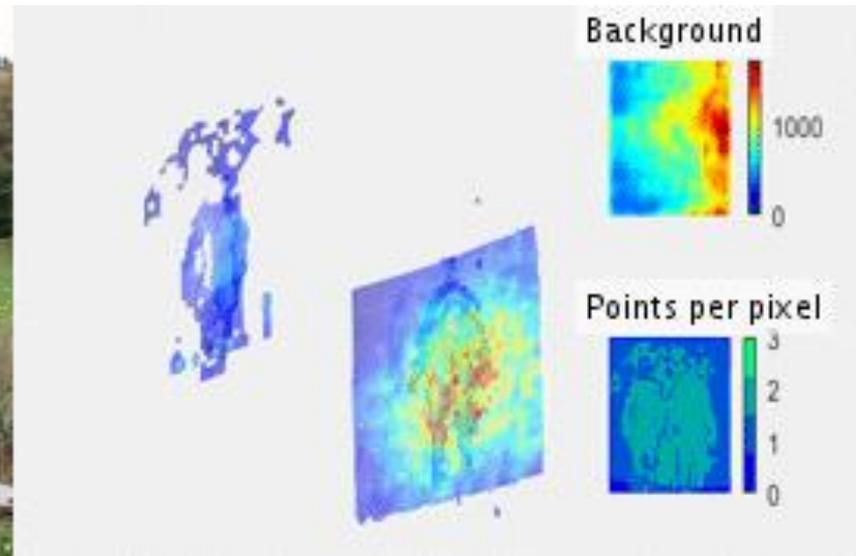
J. Tachella et al. "Real-time 3D reconstruction from single-photon lidar data using plug-and-play point cloud denoisers", Nature Comms., Nov 2019.

RT3D algorithm



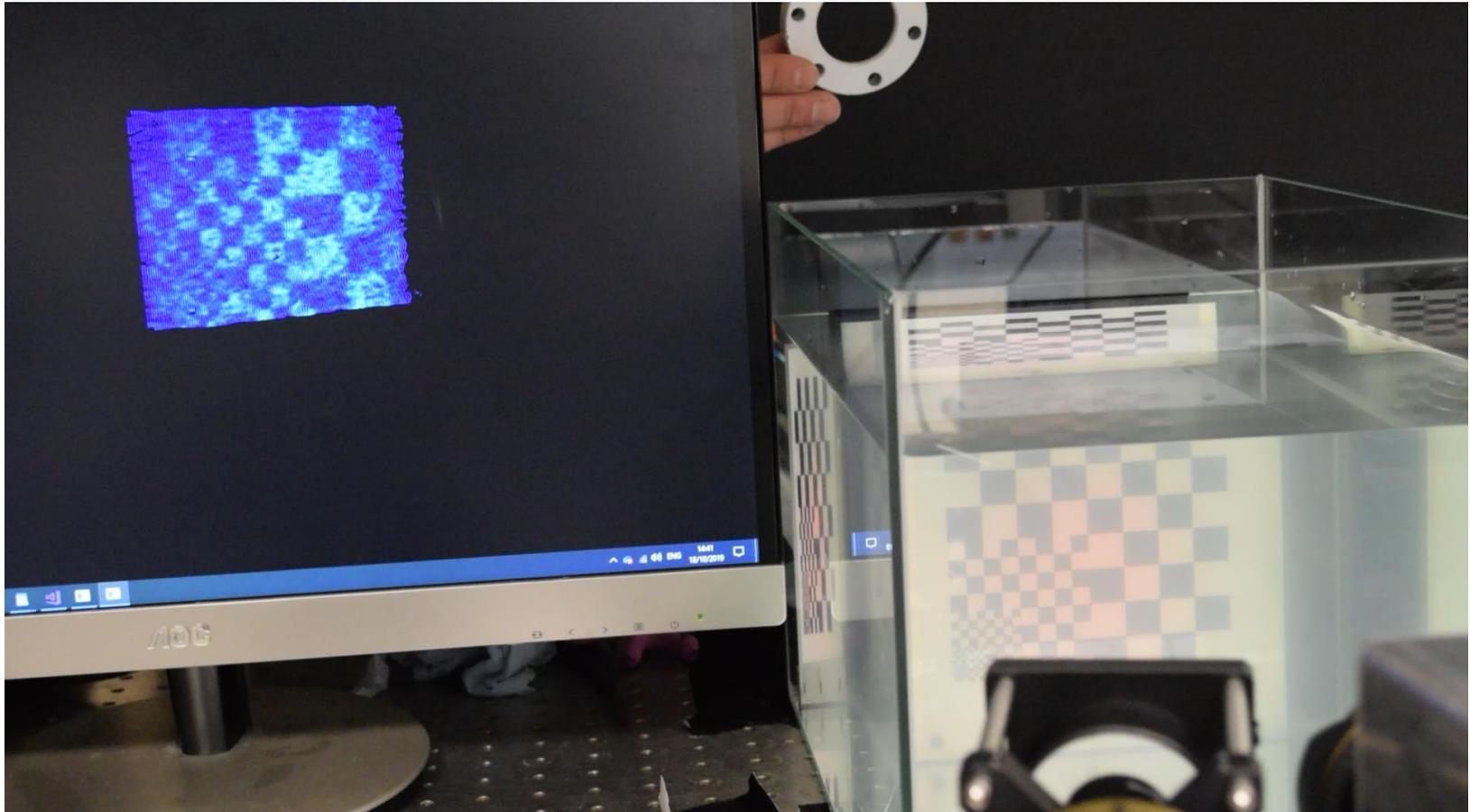
J. Tachella et al. "Real-time 3D reconstruction from single-photon lidar data using plug-and-play point cloud denoisers", Nature Comms., Nov 2019.

RT3D: distributed objects



Real-time 3D reconstruction (50 fps) from 32x32 pixels (offline).
Princeton Lightwave camera, 1550 nm
Distance: 300 m

RT3D: real-time implementation



Real-time 3D reconstruction (20 fps) from 192x128 pixels (online).
QuantiCAM, imaging through murky water
Distance: 1 m

Scalable inference

- Algorithmic structure enabling video frame rates for complex scenes
 - New opportunities
 - Adaptive processing and sensing
 - Fusion
 - Remaining challenges
 - Scalability (still)
 - Robustness/reliability

Here: regularization via temporal information + robust statistics

Bayesian online inference

- Bayesian filtering

Estimation (t)

Point cloud
+ UQ

Prediction (t+1)

Point cloud
+ UQ

Detection (t+1)

Presence map

Estimation (t+1)

Point cloud
+ UQ

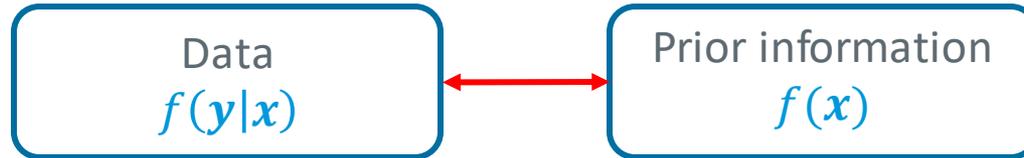
- Spatio-temporal model for prediction
- Detection for dimensionality reduction
- ~~Particle filtering~~ → variational approximation (ADF)
- Robustness?

J. Tachella et al., "Fast surface detection in single-photon Lidar waveforms", Proc. European Signal Processing Conf. (EUSIPCO), A coruna, Spain, Sept. 2019.

Y. Altmann et al., "Fast online 3D reconstruction of dynamic scenes from individual single-photon detection events", IEEE Trans. Image processing, vol. 29, 2019.

Pseudo-variational inference

Physics-inspired,
sensor-dependent
or surrogate models



Bespoke denoisers,
classifiers,...

$$f(\mathbf{x}|\mathbf{y}) \propto f(\mathbf{y}|\mathbf{x})f(\mathbf{x})$$

- Fast/efficient denoiser
- PnP approach possible in several blocks
 - PnP prior
 - PnP likelihood
- How to replace $f(\mathbf{y}|\mathbf{x})$?

Q. Legros et al., " Robust depth imaging in adverse scenarios using single-photon Lidar and beta-divergences", to appear in Proc. SSPD 2020.

Q. Legros et al., " Robust 3D reconstruction of dynamic scenes from single-photon lidar using Beta-divergence ", arxiv pre-print, 2020.

- Although not “optimal”, matched filtering (MF) works well in practice with large background
 - Fast, not iterative
 - Simple: does not require background estimation
- Here MF can be reinterpreted as a **robust estimator**

Robust inference

- Matched filter: $\{t_n\}_{n=1,\dots,N}$: set of photon ToAs

$$\max_{t_0} \left(\frac{1}{N} \sum_n g_0(t_n - t_0) \right)$$

- MLE (background-free) / LMF:

$$\max_{t_0} \left(\frac{1}{N} \sum_n \log(g_0(t_n - t_0)) \right) \Leftrightarrow \min_{t_0} (D_{KL}(\hat{f} || f_{t_0}))$$

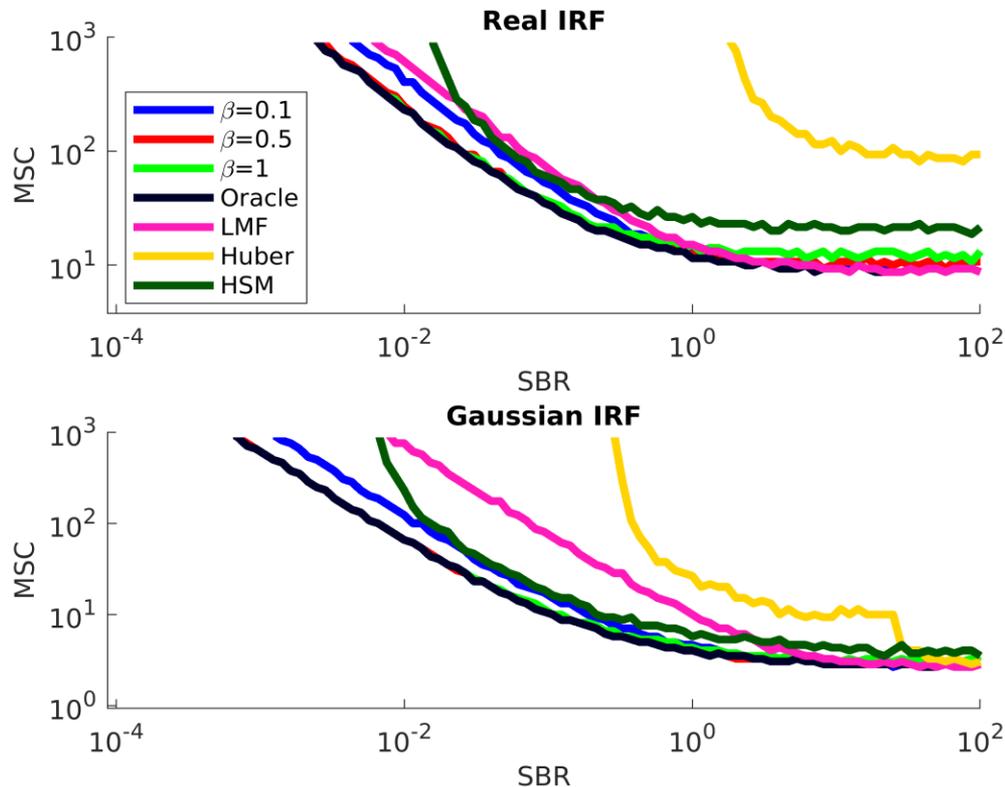
minimum KL-divergence estimator

- Robust estimator based on β -divergence

$$\max_{t_0} \frac{1}{N} \sum_n g_0(t_n - t_0)^\beta \Leftrightarrow \min_{t_0} (D_\beta(\hat{f} || f_{t_0}))$$

Pseudo-likelihood \rightarrow pseudo-posterior distribution

Comparison of estimators



Robust estimation close to oracle for $\beta \in [0.5,1]$

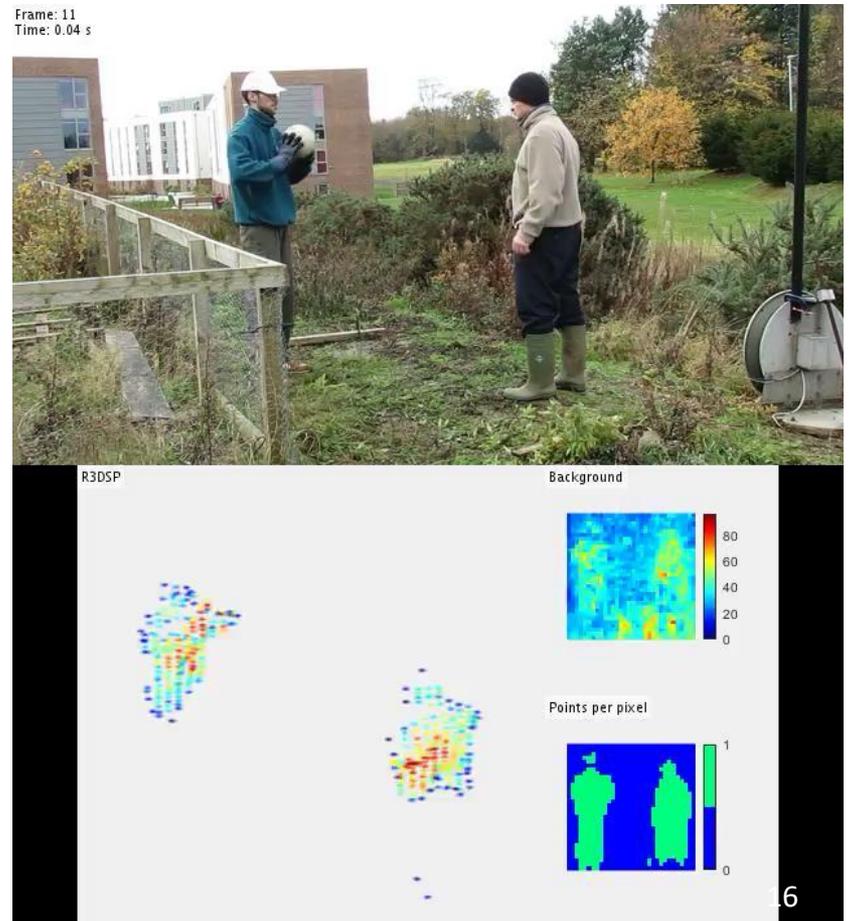
MSC: mean signal counts

SBR: signal-to-background ratio

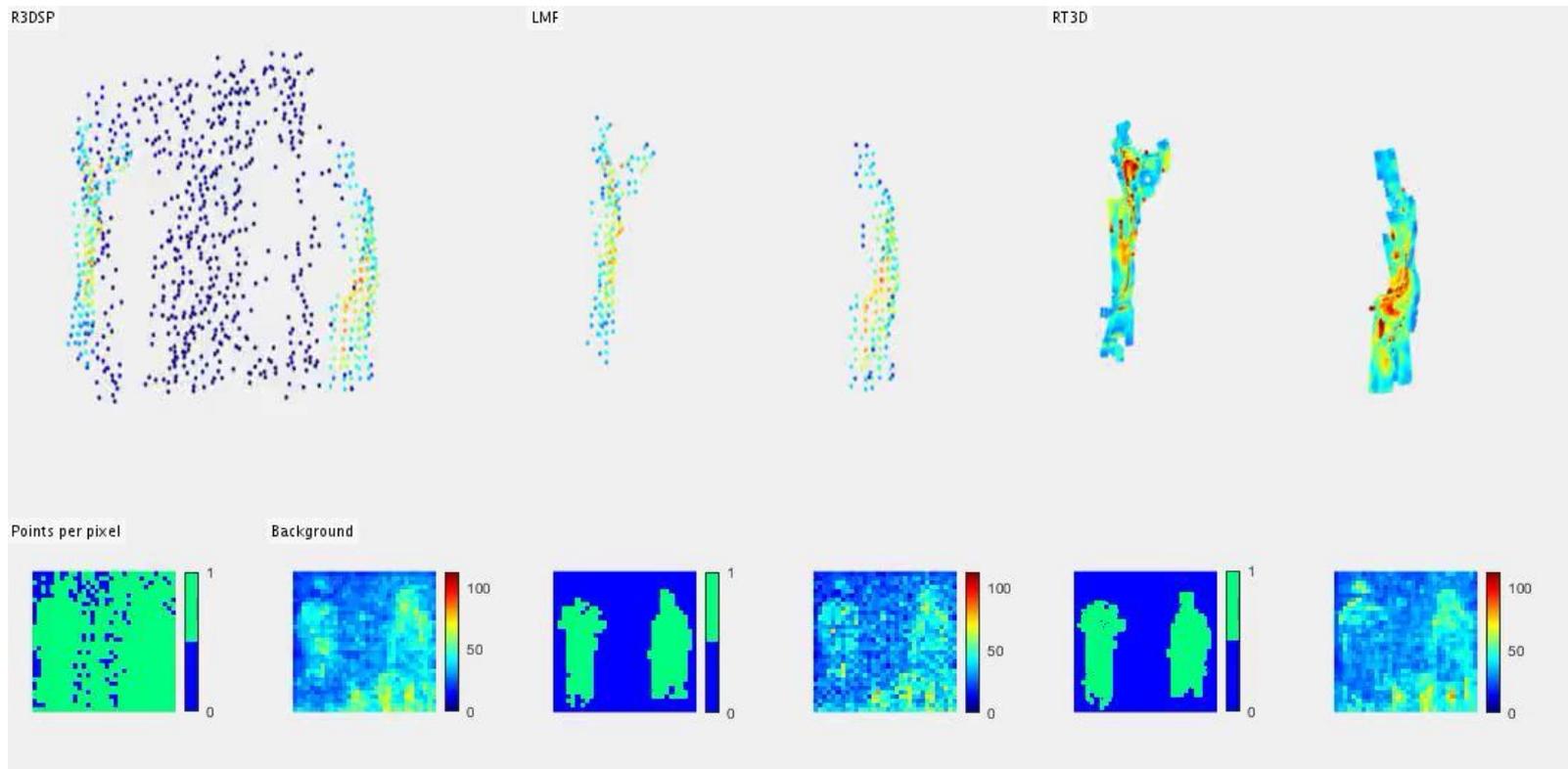
Detection threshold (> 85%) for different robust methods

Robust online 3D reconstruction

- 3D reconstruction (5000 fps) from 32x32 pixels.

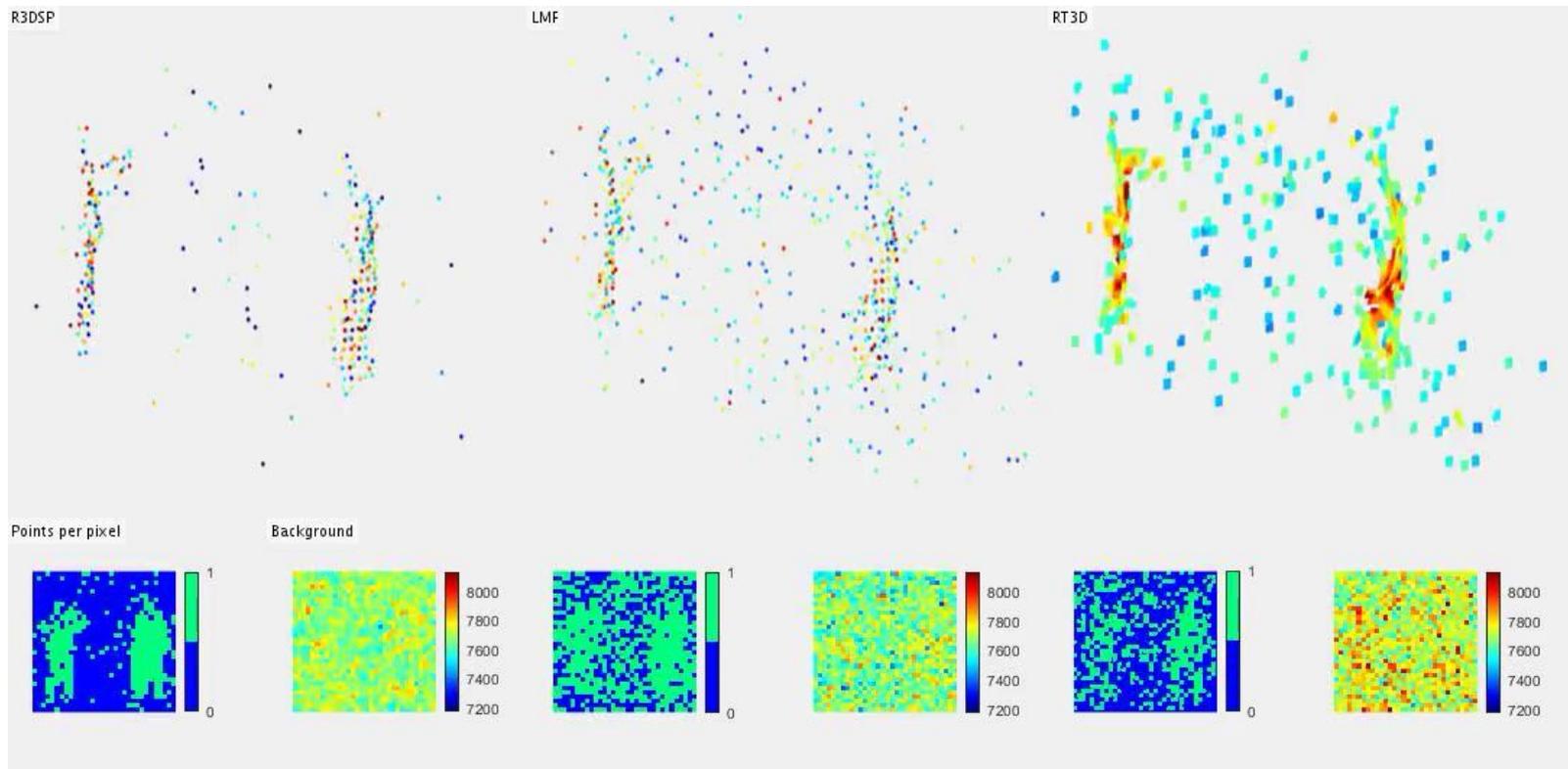


Robust online reconstruction



Online reconstruction with moderate solar illumination (MSC=55, SBR=1.6)

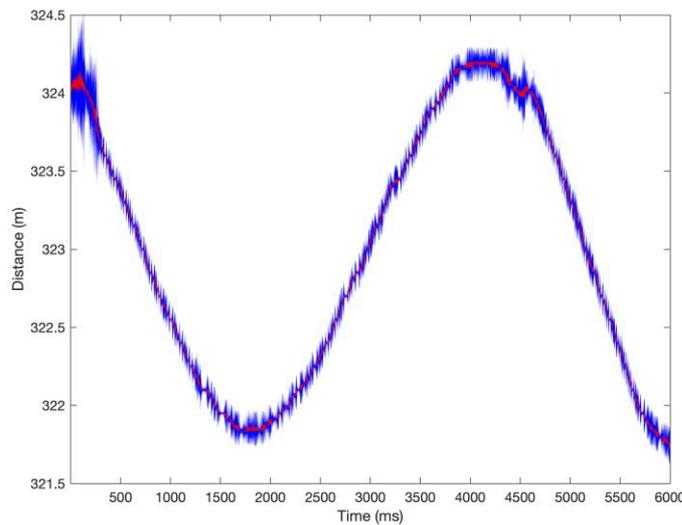
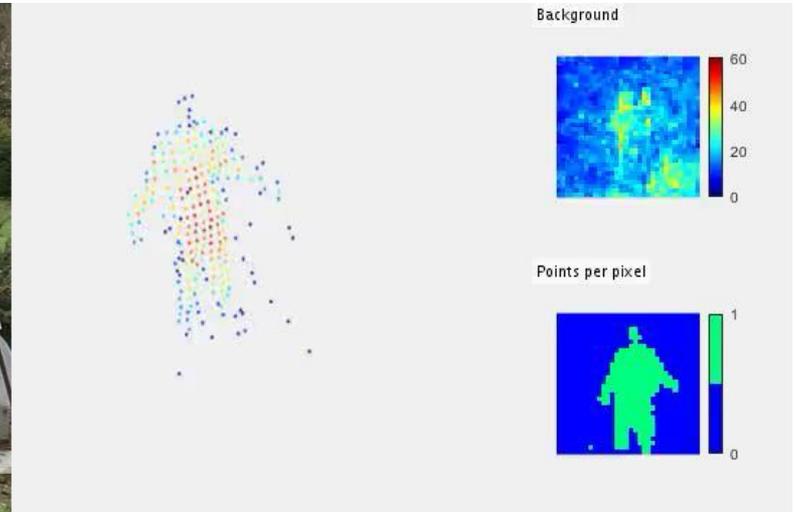
Robust online reconstruction



Online reconstruction with high solar illumination ($MSC=55$, $SBR=7.10^{-3}$)

Robust online reconstruction

Frame: 21
Time: 0.02 s



Red curve: depth posterior mean

Blue region: credible interval

Bayesian methods for online and robust 3D reconstruction

- Modular approach using approximate message passing for UQ
- PnP updates
 - Fast/scalable denoisers
 - Fast/robust “likelihood” terms
- Application-specific blocks
 - Peak-broadening, highly-scattering media

Thanks for your attention!

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