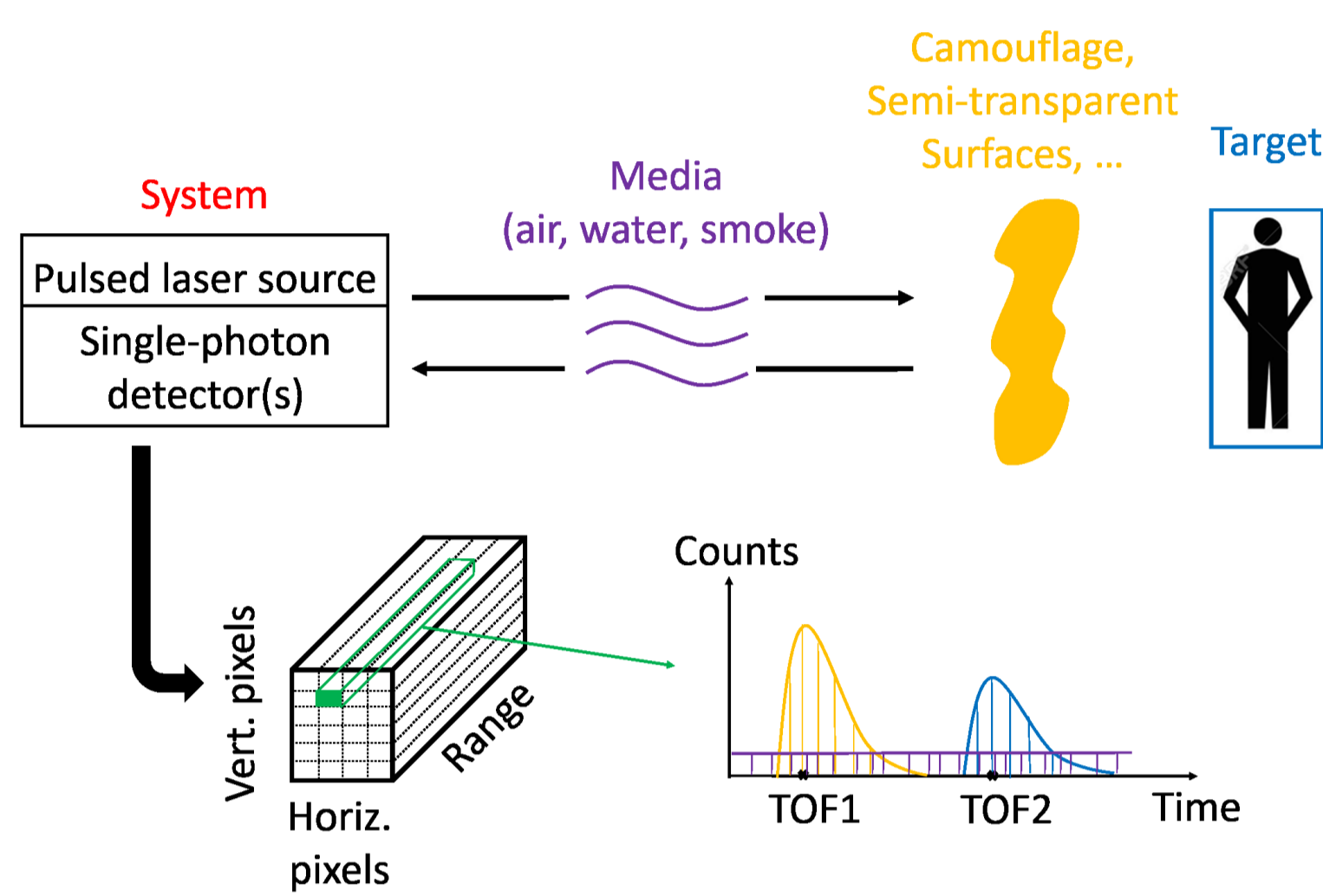


## 1. Introduction

### Problem statement

- 3D imaging using a single-photon Lidar system
- Extreme conditions: reduced acquisition time, long-range, multilayered imaging, presence of obscurants ...
- Use of spatial correlations in the observed scene.



⇒ Objectives :

- Restore the target's returns under extreme conditions
- Propose a fast algorithm suitable for real life applications

## 2. Observation model

We observe  $N$  pixels  $\mathbf{Y} = (\mathbf{y}_1, \dots, \mathbf{y}_N)$ , defined at each temporal gate  $k$  as follows:

$$y_{n,k} \sim \mathcal{P}(s_{n,k})$$

- $\mathbf{y}_n$  and  $\mathbf{s}_n$  are  $K \times 1$  vectors representing the  $n$ th observed and noiseless pixels for  $K$  time bins
- $\mathcal{P}(\cdot)$  denotes the Poisson distribution

### Parametric model

$$s_{n,k} = \sum_{m=1}^{M_n} [r_{n,m} g_0(k - k_{n,m})] + b_n \quad (1)$$

- $r_{n,m}$ ,  $k_{n,m}$  are the reflectivity and depth position of the  $m$ th object
- $b_n$  is the background noise
- $g_0$  is the system impulse response
- $M_n$  is the number of objects in the  $n$ th pixel

### Equivalent formulation

$$\mathbf{s}_n = \mathbf{G}^{(1)} \mathbf{x}_n(r_n, \mathbf{k}_n, b_n) \quad (2)$$

$$\begin{bmatrix} s_{n,1} \\ \vdots \\ s_{n,K} \end{bmatrix} = \begin{bmatrix} g_1 & \dots & g_{k_{n,m}} & \dots & g_K \\ \vdots & & \vdots & & \vdots \\ \vdots & & \vdots & & \vdots \\ \vdots & & \vdots & & \vdots \end{bmatrix} \times \begin{bmatrix} 0 \\ \vdots \\ r_{n,m} \\ \vdots \\ r_{n,m} \\ \vdots \\ 0 \\ \vdots \\ b_n \end{bmatrix} \begin{matrix} k_{n,m'} \\ k_{n,m} \\ k_{n,m} \\ k_{n,m} \\ k_{n,m} \\ k_{n,m} \\ k_{n,m} \\ k_{n,m} \\ k_{n,m} \end{matrix}$$

$$\mathbf{x}_n \quad (K+1) \times 1$$

- $g_{k_{n,m}}$  represents  $g_0$  shifted by  $k_{n,m}$
- $\mathbf{X}$  is a  $(K+1) \times N$  matrix containing the parameters of interest

### Prior Knowledge/Hypotheses on $\mathbf{X}$

- The elements of  $\mathbf{X}$  are non-negative
- *Hyp. 1:* For local regions, a small number of depths are active with respect to the range window ( $M_n \ll K, \forall n$ )
- *Hyp. 2:* The observed objects present spatial correlations

## 3. Proposed Restoration Approach

### Cost function

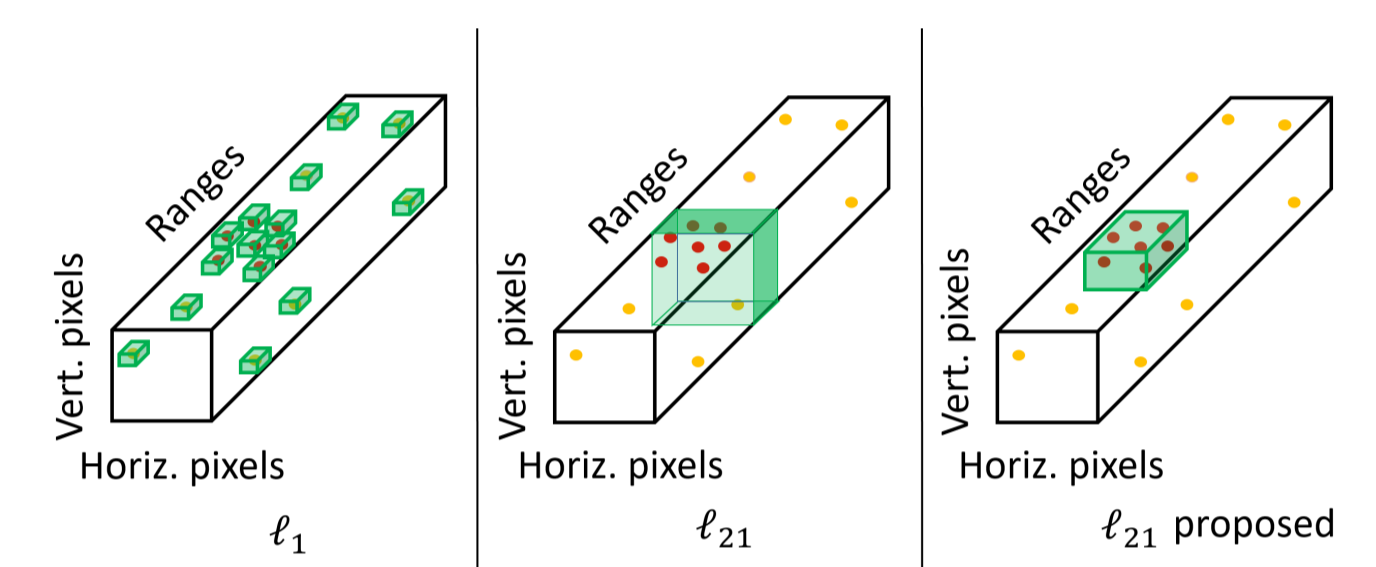
$$\underset{\mathbf{X}}{\operatorname{argmin}} \mathcal{L}(\mathbf{X}) + i_{\mathbb{R}_+}(\mathbf{X}) + \tau_1 \phi_{\mathbf{v}}(\mathbf{X}) + \tau_2 \psi_{\mathbf{w}}(\mathbf{X})$$

- $\tau_1 > 0, \tau_2 > 0$  are fixed regularization parameters
- $\mathbf{v} > 0, \mathbf{w} > 0$  are fixed weight vectors
- $i_{\mathbb{R}_+}(\mathbf{X})$  is the indicator function that imposes positivity on  $\mathbf{X}$

### Data statistics $\mathcal{L}(\mathbf{X})$ (negative log-likelihood)

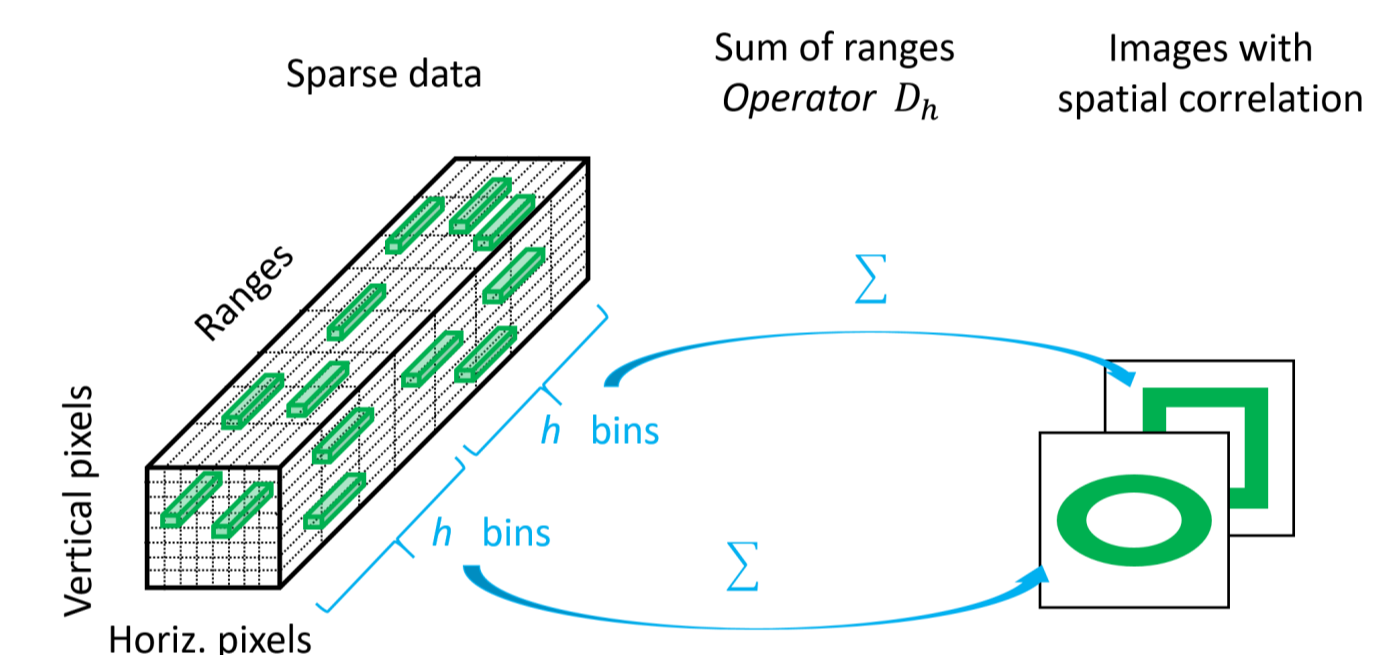
$$\mathcal{L}(\mathbf{X}) = \sum_{n=1}^N \sum_{k=1}^K \{s_{n,k}(\mathbf{x}_n) - y_{n,k} \log[s_{n,k}(\mathbf{x}_n)]\}$$

### *Hyp. 1:* Depth regularization $\phi_{\mathbf{v}}(\mathbf{X}) = \|\mathbf{K}_v \mathbf{X}\|_{2,1}$



(Left) model in [1], (middle) model in [2], (right) proposed model

### *Hyp. 2:* Intensity regularization $\psi_{\mathbf{w}}(\mathbf{X}) = \|\mathbf{H}_w \mathbf{D}_h \mathbf{X}\|_1$



## 4. Estimation algorithm using ADMM

### Our Problem

$$\underset{\mathbf{X}}{\operatorname{argmin}} \mathcal{H}(\mathbf{G}^{(1)} \mathbf{X}) + i_{\mathbb{R}_+}(\mathbf{X}) + \tau_1 \phi_{\mathbf{v}}(\mathbf{X}) + \tau_2 \psi_{\mathbf{w}}(\mathbf{X})$$

with  $\mathcal{L}(\mathbf{X}) = \mathcal{H}(\mathbf{G}^{(1)} \mathbf{X})$

### Equivalent formulation

$$\underset{\mathbf{X}, \mathbf{V}}{\operatorname{argmin}} \mathcal{H}(\mathbf{V}_1) + i_{\mathbb{R}_+}(\mathbf{V}_2) + \tau_1 \|\mathbf{V}_3\|_{2,1} + \tau_2 \|\mathbf{V}_5\|_1$$

subject to  $\mathbf{A}\mathbf{X} + \mathbf{B}\mathbf{V} = \mathbf{0}$  and

$$\mathbf{A} = \begin{bmatrix} \mathbf{G}^{(1)} \\ \mathbf{I}_{K+1} \\ \mathbf{K}_v \\ \mathbf{D}_h \\ \mathbf{0} \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} -\mathbf{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & -\mathbf{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & -\mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & -\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{H}_w & -\mathbf{I} \end{bmatrix}$$

### Alternating direction method of multipliers algorithm

Initialize  $\mathbf{V}_j^{(0)}, \mathbf{F}^{(0)}, \forall j, \mu$ . Set  $i \leftarrow 0, \text{conv} \leftarrow 0$

**while** conv=0 **do**

Linear system of equations

Update  $\mathbf{X}^{(i+1)}$  by solving a linear system of equations

Moreau proximity operators

Update  $\mathbf{V}_j^{(i+1)}, \forall j \in \{1, \dots, 5\}$  by evaluating their analytical proximal operators

Update Lagrange multipliers

$\mathbf{F}^{(i+1)} \leftarrow \mathbf{F}^{(i)} - \mathbf{A}\mathbf{X}^{(i+1)} - \mathbf{B}\mathbf{V}^{(i+1)}$

conv ← 1, if the stopping criterion is satisfied.

$i \leftarrow i + 1$

**end while**

where  $\mathbf{F}$  denotes the Lagrange multipliers

## 5. Results on synthetic data

### Synthetic bowling scene (see Fig. 1-left)

- $123 \times 139$  pixels, and 300 time bins
- Interval of averaged signal Photon-Per-Pixel (PPP):  $[0.2, 5]$  ppp
- Interval of Signal to Background (SBR) level:  $[0.05, 1.25]$
- Comparison with:
  - **Class.**: classical cross-correlation algorithm
  - **BFC**: Class. algorithm applied to background-free data
  - **NR3D**: Proposed Nonlocal Restoration of 3D images

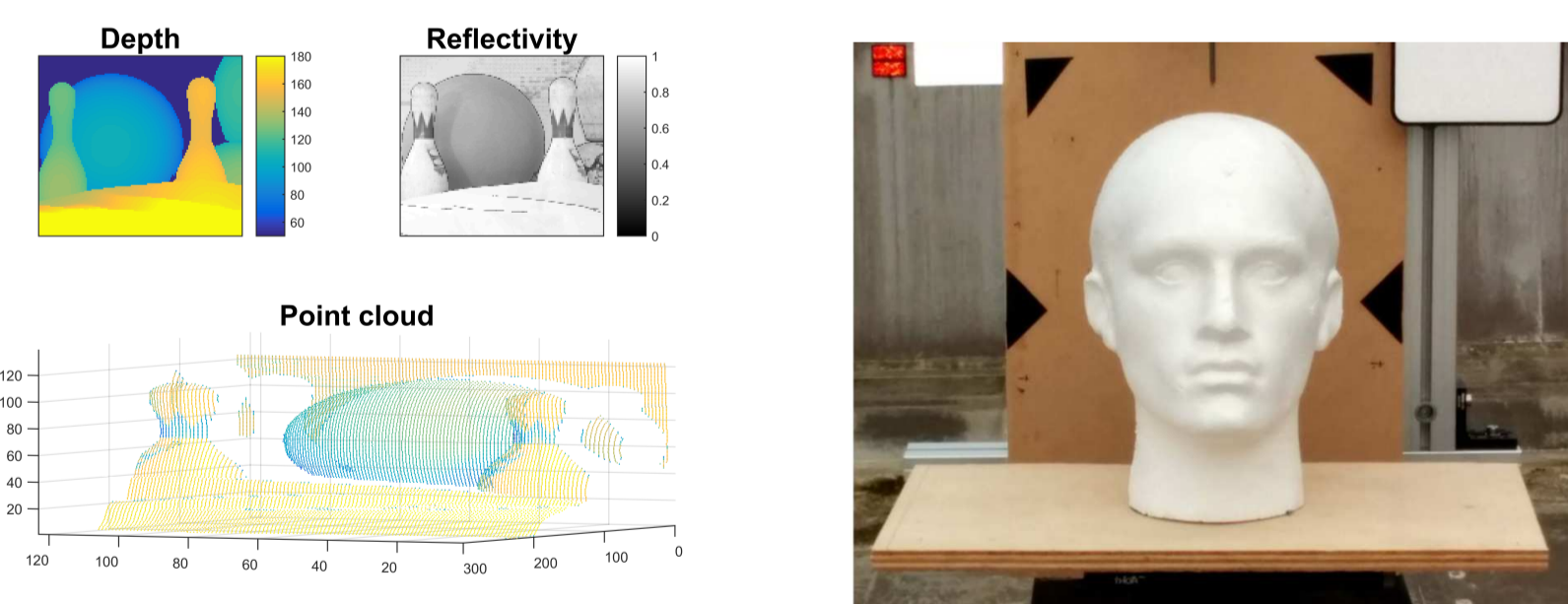


Fig. 1: (Left) Synthetic bowling scene. (Right) Picture of the real target (acquired with  $142 \times 142$  pixels).

### SRE (in dB) results with respect to SBR and PPP

Signal PPP		5	2	0.8	0.4	0.2
SBR		1.25	0.5	0.2	0.1	0.05
Depth	Class.	11.5	5.3	2.9	2.2	1.9
	BFC	19.8	14.0	11.0	7.5	5.0
	NR3D	19.8	14.0	11.0	7.5	5.0
Reflect.	Class.	6.6	1.4	-6.5	-13.1	-19.6
	BFC	7.3	3.5	-0.4	-3.5	-6.9
	NR3D	13.3	13.0	8.4	9.8	3.2

## 6. Results on real data

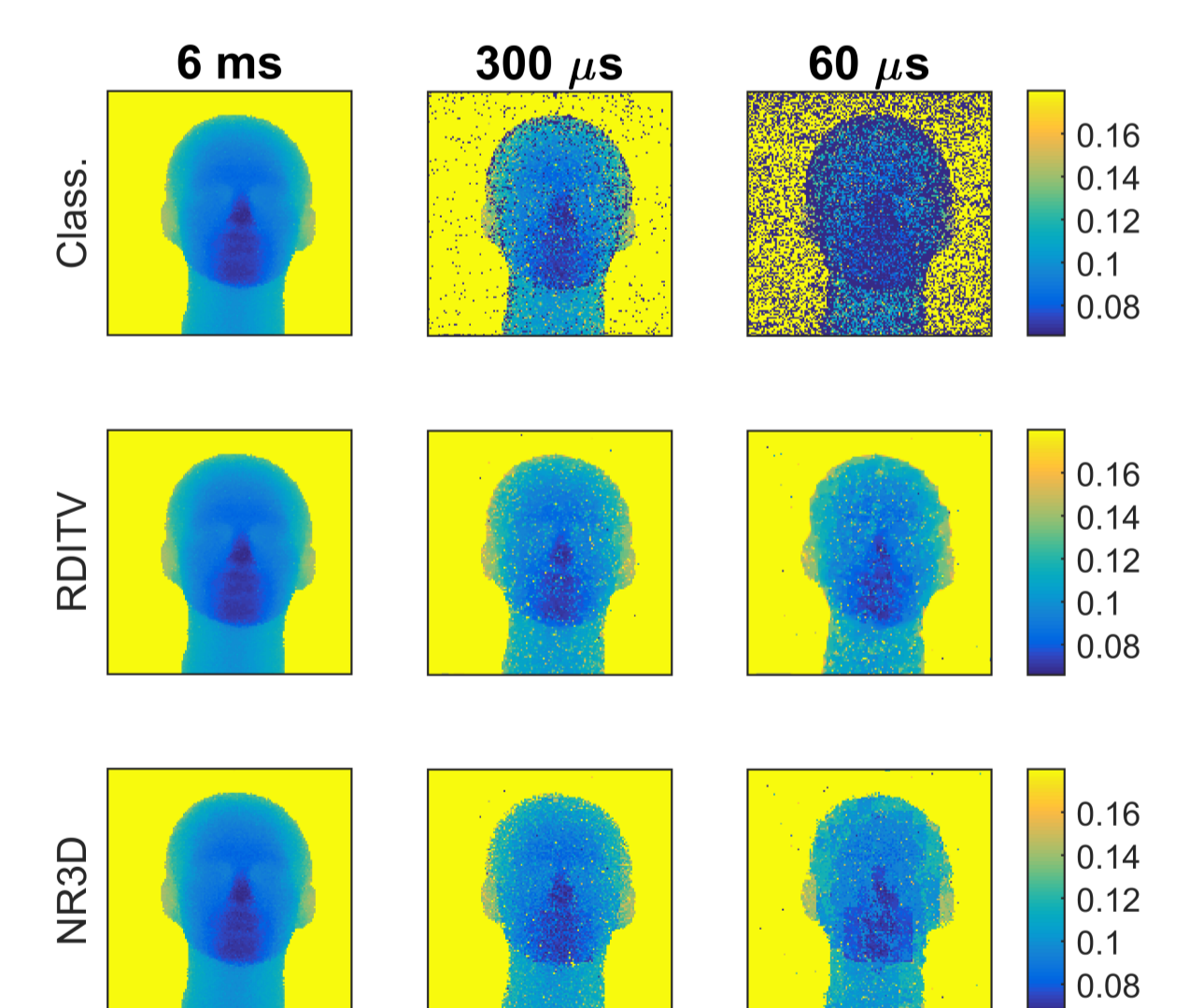


Fig. 2: Depth maps for reduced acquisition times-per-pixel (comparison with RDITV [3])

## 7. Future work

- Generalize to high-dimensional data (multi-frames, multi-wavelengths)
- Set the weights  $\mathbf{v}, \mathbf{w}$  using other acquisition modalities to perform multi-modal data fusion

## References

- [1] D. Shin, F. Xu, F. N. C. Wong, J. H. Shapiro, and V. K. Goyal, "Computational multi-depth single-photon imaging," *Opt. Express*, vol. 24, no. 3, pp. 1873-1888, Feb 2016.
- [2] A. Halimi, R. Tobin, A. McCarthy, S. McLaughlin, and G. S. Buller, "Restoration of multi-layered single-photon 3D lidar images," in *Proc. EUSIPCO*, 2017, pp. 708-712.
- [3] A. Halimi, Y. Altmann, A. McCarthy, X. Ren, R. Tobin, G. S. Buller, and S. McLaughlin, "Restoration of intensity and depth images constructed using sparse single-photon data," in *Proc. EUSIPCO*, 2016, pp. 86-90.