Target detection for depth imaging using sparse single-photon data

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1. Introduction

Depth imaging using single-photon Lidar

- Active imaging using pulsed-lasers
- Accurate depth/range resolution (< centimeters at several hundreds of meters in air)

☞ 3D image reconstruction

- Long range imaging (defence)
- Building monitoring (heritage convervation)
- Environmental sciences: forest monitoring
- Underwater imaging

Single-surface observation model

- observed Lidar waveform $\mathbf{y}_{i,j} = [y_{i,j,1}, \ldots, y_{i,j,T}]^T$

$$y_{i,j,t} | r_{i,j}, t_{i,j}, b_{i,j} \sim \mathcal{P}\left(r_{i,j} g_0 \left(t - t_{i,j}\right) + b_{i,j}\right)$$

- $y_{i,j,t}$: photon count within the tth bin of the pixel (i,j)
- $b_{i,j} > 0$: background and dark photon level
- $t_{i,j}$: position of an object (if present) at a given range from the sensor
- $r_{i,j}$: object reflectivity
- $g_0(\cdot) > 0$: instrumental impulse response

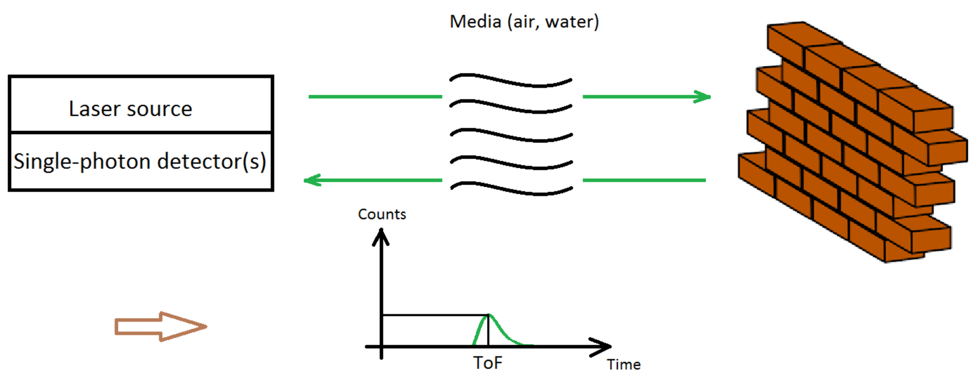

Fig. 1: Single-photon Lidar principle.

Target detection problem

- Usually performed during post-processing (reflectivity thresholding)
- Estimation and detection performance highly dependent on the background levels
- Severe performance degradation in the limit of low "useful" detections

Model selection problem

- observed pixel spectrum

$$y_{i,j,t} | z_{i,j} = 0, \boldsymbol{\theta}^0_{i,j} \sim \mathcal{P}\left(b_{i,j}\right) \quad (1)$$

$$y_{i,j,t} | z_{i,j} = 1, \boldsymbol{\theta}^1_{i,j} \sim \mathcal{P}\left(r_{i,j} g_0 \left(t - t_{i,j}\right) + b_{i,j}\right) \quad (2)$$

- $z_{i,j}$: binary label for target detection
- $\boldsymbol{\theta}^0_{i,j} = r_{i,j} \in \mathbb{R}^+$
- $\boldsymbol{\theta}^1_{i,j} = [r_{i,j}, t_{i,j}, b_{i,j}] \in \mathbb{R}^+ \times \mathbb{T} \times \mathbb{R}^+$
- $\mathbb{T}$: admissible set of target ranges

Proposed method: Joint target detection and depth/reflectivity estimation using Bayesian inference

2. Proposed Bayesian model

Likelihoods

- Defined by (2) and (3)

Parameter prior distributions

- Background levels: Gamma Markov random [1, 2] to capture spatial dependencies affecting the ambient illumination
  Improves the parameter estimation in the limit of few detected counts.
- Depth/range parameters:
  Uniform prior distributions $p(t_{i,j} = t | z_{i,j} = 1)$ to reflect the lack of knowledge about the 3D structure of the scene
- Reflectivity coefficients:
  Hierarchical prior model using conjugate gamma/inverse-gamma priors

$$r_{i,j} | \alpha, \beta \sim \mathcal{G}(\alpha, \beta), \quad \forall (i,j)$$
$$\alpha | \alpha_1, \alpha_2 \sim \mathcal{G}(\alpha_1, \alpha_2)$$
$$\beta | \beta_1, \beta_2 \sim \mathcal{IG}(\beta_1, \beta_2)$$

- Detection/model selection labels:
  Ising model

$$f(\mathbf{Z}|c) \propto \exp\left[c\phi(\mathbf{Z})\right]$$

- $\phi(\mathbf{Z}) = \sum_{i,j} \sum_{(i',j') \in \mathcal{V}_{i,j}} \delta\left(z_{i,j} - z_{i',j'}\right)$
- $\delta(\cdot)$: Kronecker delta function
- $\mathcal{V}_{i,j}$: set of neighbours of pixel (i,j)
- c: spatial granularity parameters

Joint posterior distribution

$$f(\mathbf{Z}, \boldsymbol{\Theta}, \alpha, \beta | \mathbf{Y}, c) \propto \left[\prod_{i,j} f(\mathbf{y}_{i,j} | z_{i,j}, \boldsymbol{\theta}_{i,j}) f(\boldsymbol{\theta}_{i,j} | \mathbf{Z}, \alpha, \beta)\right] \times f(\mathbf{Z}|c) f(\alpha) f(\beta).$$

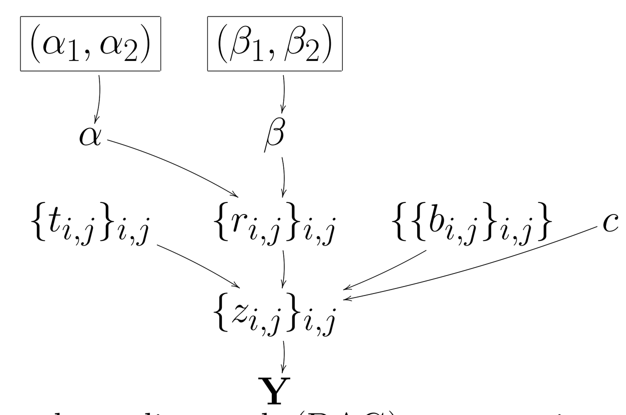

Fig. 2: Directed acyclic graph (DAG) representing the proposed hierarchical Bayesian model.

3. Reversible-Jump Markov chain Monte Carlo algorithm

- Bayesian estimation in union of subspaces
- Pixel-wise model selection but...
- Dependencies between pixels (spatial correlation)

⇒ MCMC method for global Bayesian inference

Moves within a subspace

- Updating $b_{i,j}$ and $r_{i,j}$: standard Gibbs step (conditional distr. → mixtures of gamma distributions)
- Updating $t_{i,j}$: Sampling from a discrete distribution (finite support)

Moves between subspaces

- Move from $z_{i,j} = 0$ to $z_{i,j} = 1$:
  Proposal distribution designed to generate candidates in regions of high prob. → High acceptance rate (good mixing properties)

Other parameters

- Updating β: standard Gibbs step (conditional distr. → inverse-gamma)
- Updating α: Metropolis-Hastings step (non-standard conditional distr.)
- Updating c: stochastic gradient (during burn-in) [3]

4. Results

Data acquisition

- Detection of a life-sized polystyrene head at 325m
- 3 acquisitions : noon, 3p.m., and 8.pm
- Different acquisition times per pixel

		Acquisition Time			
		300μs	1ms	3ms	30ms
Av. photon counts	noon	5.6	18.5	55.5	554.6
	3 p.m.	4.1	13.7	41.0	408.9
	8 p.m.	1.2	4.9	11.6	116.0
Empty pixels (%)	noon	2.79	< 0.01	0	0
	3 p.m.	4.2	0.02	0	0
	8 p.m.	61.8	52.2	40.4	2.2

Table 1: Average number of detected photons per pixel and proportion of empty pixels for the different acquisitions.

Detection performance

			π_{00}	π_{10}	π_{01}	π_{11}
noon	3ms	X-corr	79.9	20.1	8.9	91.1
		Prop. algo.	99.9	0.01	10.8	89.2
	1ms	X-corr	57.4	42.6	16.9	83.1
		Prop. algo.	99.9	0.01	18.6	81.4
	0.3ms	X-corr	59.6	40.4	39.1	60.9
		Prop. algo.	99.9	0.01	20.4	79.6

Table 2: Detection performance (prob. in %)

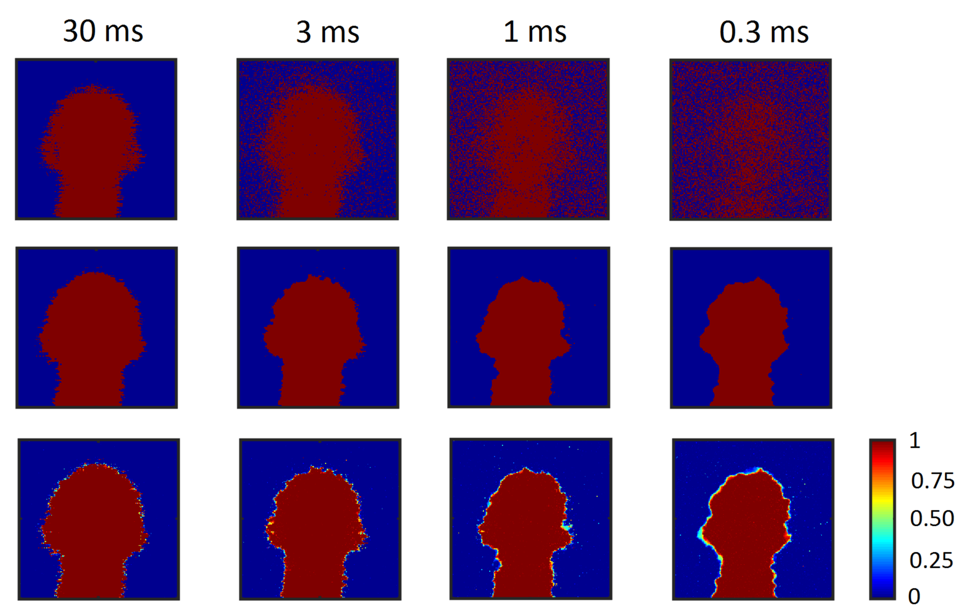

Fig. 3: Example of detection (noon) results obtained by the standard (top) and proposed (bottom) method.

Estimation performance

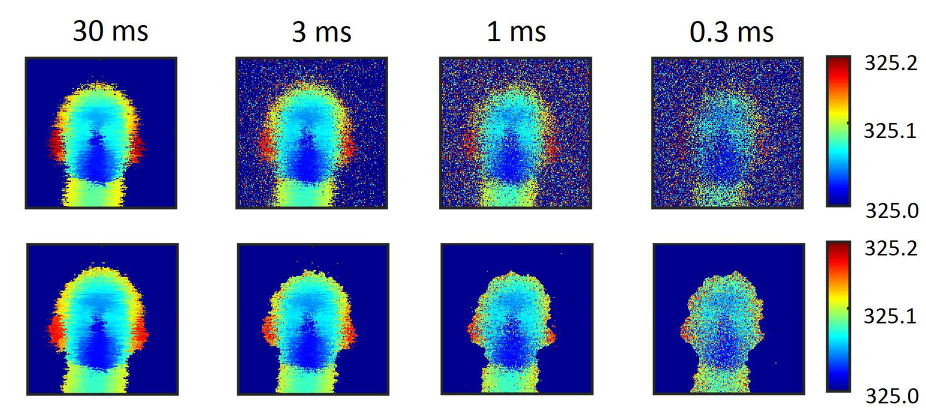

Fig. 4: Target ranges estimated by the standard (top) and proposed (bottom) method.

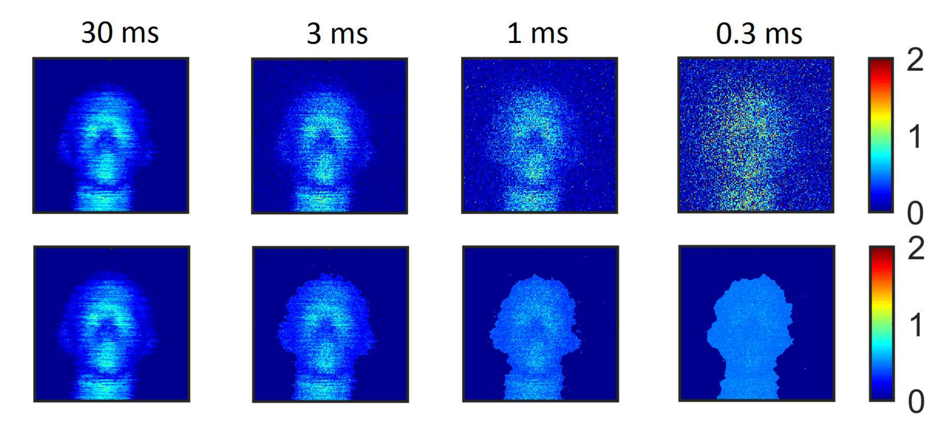

Fig. 5: Target reflectivity (noon) estimated by the standard (top) and proposed (bottom) method.

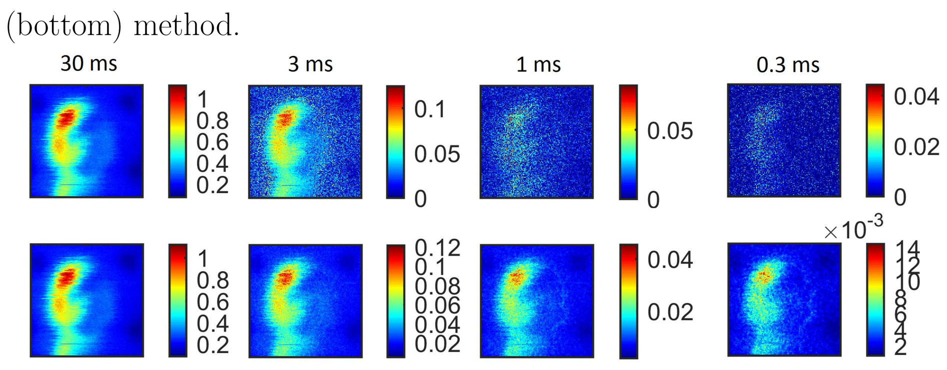

Fig. 6: Background levels (noon) estimated by the standard (top) and proposed (bottom) method.

References

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