High Photon Efficiency Computational Range Imaging using Spatio-Temporal Statistical Regularization

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Abstract: We demonstrate 1 photon-per-pixel photon efficiency and sub-pulse-width range resolution in megapixel laser range imaging by using a joint spatio-temporal statistical processing framework and by exploiting transform-domain sparsity.

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Laser radar or light detection and ranging (LIDAR) systems allow range estimation at low light levels using raster-scanned, pulsed illumination followed by measurement of the backscattered light using time-correlated single-photon counting detection [1]. For each pixel position in a 2-D range image, the corresponding scene point is illuminated with a series of laser pulses. We consider the case in which the number of reflected photons incident at the detector is much smaller than the number of transmitted pulses. At such low light levels, the photon arrival statistics are modeled using time-inhomogeneous Poisson point processes, where the rate function is determined by the pulse shape [2]. In traditional LIDAR operation at low light level, a large number of photon detections is necessary at each pixel position to compute an accurate estimate of range from a histogram of detected arrival times. The resulting long dwell times limit the real-time performance of LIDAR systems and lower the achievable spatial resolution by fast raster scanning.

Data processing in traditional LIDAR systems is accomplished using *pointwise* maximum likelihood (ML) range estimation methods [1, 3], without exploiting any spatial correlation between neighboring scene points. In reality, natural scenes possess a great degree of spatial structure—in depth even more so than in reflectance—which is often described using sparsity in appropriate transform domains, such as wavelet or Fourier bases. In the context of LIDAR, sparsity has been employed to further denoise depth images, after the pointwise ML range estimation step [4].

We introduce a joint spatio-temporal statistical estimation framework to accurately acquire scene depth with high range resolution from a small number of photon time-of-arrival measurements at each pixel—even a single time-of-arrival per pixel. Compared with the conventional two-step procedure of pointwise ML range estimation followed by spatial denoising, our method achieves better range resolution with fewer photon measurements by enforcing transform-domain regularization in the transverse dimensions simultaneously with range estimation.

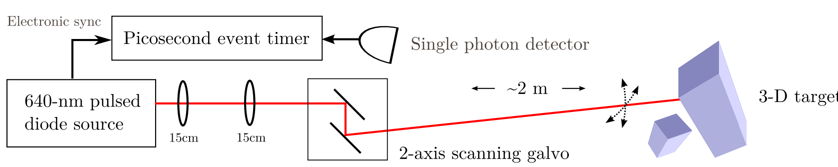

Fig. 1. Experimental setup.

Experimental setup: We illuminate a target using a PicoQuant 640-nm, 200-ps, 0.6-mW pulsed laser with a 10-MHz repetition rate and raster-scan with a two-mirror scanning galvo system. The range-imaging target is placed at a distance of 1.5 to 2 m from the source. Detection is performed using a lensless Micro Photon Devices PDM series single-photon detector with an active area of 100×100 μm, detection efficiency of 35% and timing resolution under 50 ps. We employ a 2-nm bandwidth, free-space interference filter with a peak transmission of 49% to filter out stray light. Time-resolved detection of each photon count is performed with a resolution of 8-ps using a PicoQuant HydraHarp system. We scan a 1000×1000 pixel raster image and utilize only the first photon arrival at every pixel for data processing purposes, with pixel dwell time limited only by the mechanical speed of the galvo system.

Data processing technique: Suppose scene point i at distance d_i from the ranging device has reflectance a_i. Assuming no multipath reflections and no contribution from other laser pulses, when the laser pulse shape is $s(t)$, the intensity of reflected light at the detector is well modeled as $r(t) = a_i\, s(t - 2d_i/c) + b$, where c is the speed of light and b combines the constant background intensity and dark count rate. For detector quantum efficiency η, the detected photon arrival times obey Poisson point process statistics with rate $\lambda(t) = \eta\, r(t)$. The reflected light is incident on a single-photon counting detector which is synchronized with outgoing laser pulses for time-of-flight measurements with an accuracy of Δ picoseconds in the photon-arrival time stamps. Denote by Y_{ij} the integer-valued random variable representing the time bin of the jth detected photon arrival. One can show that under the conditions of low background and dark count rates ($b \approx 0$) and at most one detected photon per pulse, the likelihood function of Y_{ij} approximately satisfies $\Pr[Y_{ij} = k; d_i] \propto s(k\Delta - 2d_i/c)$.

LIDAR systems conventionally record a large number N_i of photon arrivals (binned to time resolution Δ) for each scene point i. The index of the peak of a histogram of arrival times then easily gives an estimate for d_i, but this is accurate only when N_i is quite large. A more sophisticated technique combines the arrival times to form a joint likelihood for the N_i photon arrivals taken together; this leads to a pointwise ML estimate $\hat{d}_i = \arg\max_d \sum_{j=1}^{N_i} \Pr[Y_{ij} = k_j; d] = \arg\max_d \sum_{j=1}^{N_i} s(k_j\Delta - 2d/c)$, which enables reasonable range estimates for lower values of N_i.

The key to our processing technique is to perform simultaneous spatio-temporal estimation of $\mathbf{D} = [d_1, \ldots, d_M]$, where M is the total number of transverse scene points. Specifically, we compute $\hat{\mathbf{D}} = \arg\max_D \sum_{i=1}^{M} \sum_{j=1}^{N_i} \log s(k_j\Delta - 2d_i/c) + \alpha\|\Phi D\|_1$, where Φ represents an inverse discrete wavelet transform and α is a positive real parameter. The first term in the objective corresponds to the likelihood and the second term enforces transverse spatial structure across the different pixel values. In our proof-of-principle experiments, α is chosen to minimize the mean square error (MSE) between estimate and ground truth image. Traditional depth map denoising assumes an additive Gaussian noise perturbation to the true range data, which at low light levels performs poorly; the aforementioned likelihood function, $\Pr[Y_{ij} = k; d]$, represents a more accurate model of noisy observations.

Results: A depth map produced with about 1000 photons per pixel is effectively ground truth (Fig. 2(a)). The first arrival at each pixel, without processing, results in very poor depth maps (Fig. 2(b)); the top row shows a 30 mm feature is resolvable, commensurate with the 200 ps pulse width. Our processing produces an accurate depth map from processing the same single-photon per pixel data (Fig. 2(c)); the top row shows sub-pulse-width resolution and both rows show about 30 dB noise reduction. Conventional processing treats the deviations between the raw data and ground truth as Gaussian noise (Fig. 2(d)); this is dramatically less effective.

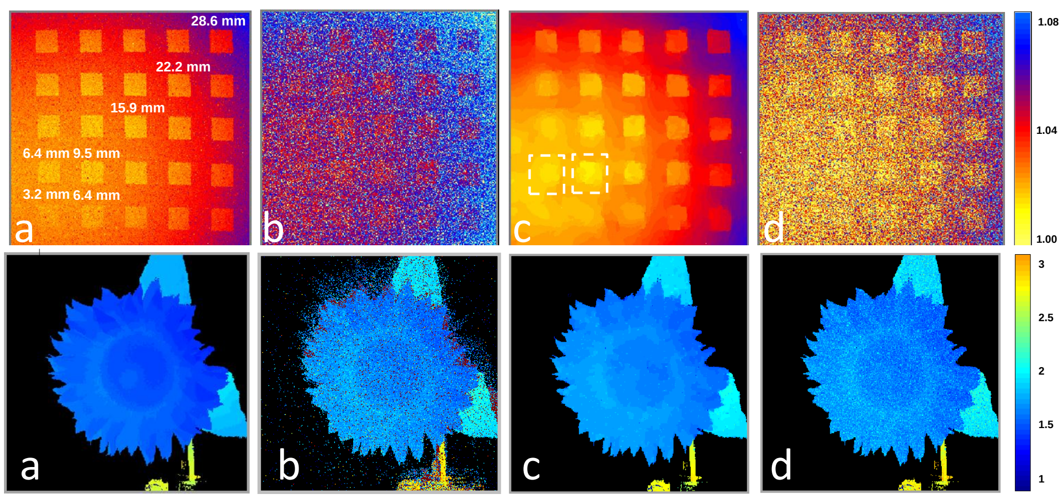

Fig. 2. (a) Ground truth (b) Single photon range estimate [MSE = 100.3 dB (top) and 107.1 dB (bottom)] (c) using our new spatio-temporal regularization model [MSE = 70.9 dB (top) and 78.7 dB (bottom)] (d) using traditional denoising [MSE = 89.4 dB (top) and 103.1 dB (bottom)].

Conclusion: We present and experimentally demonstrate a statistical framework for high photon efficiency laser range imaging and compare results using traditional range imaging using only 1 photon arrival per pixel. This enables us to not only reduce noise significantly but also improve resolution beyond the pulse width by making assumptions about spatial sparsity in natural scenes. By improving photon efficiency we drastically reduce pixel dwell time, and demonstrate the possibility of practical, high-speed megapixel-resolution range imaging in low light.

References

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