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Photon-efficient computational imaging with a single-photon camera

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Abstract: Using a photon-efficient reconstruction algorithm and a single-photon camera prototype, we demonstrate accurate depth and reflectivity imaging of natural scenes from an average of ∼1 detected signal photon per pixel.

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Introduction. Active optical systems for 3D imaging typically require a large number of photon detections (e.g., more than 10^3 photons per pixel) to suppress photon noise inherent in the optical detection process. However, in remote sensing such as light detection and ranging, as well as in biomedical imaging, limitations on the optical flux and data-collection time preclude the collection of such a large number of photons. An outstanding challenge in such scenarios is to make use of a small number of photon detections to accurately recover the desired scene information.

First-photon imaging (FPI) [1] demonstrated state-of-the-art photon-efficient 3D imaging by using only the first detected photon for each pixel, but its raster-scanning setup required exactly one photon detection at every pixel, resulting in a low frame-rate and making each pixel’s acquisition time a random variable. Consequently, FPI is not applicable to operation using a single-photon camera, whose single-photon avalanche diode (SPAD) detector array [2, 3] requires that all of its pixels have the same acquisition time. Recently, theoretical extensions of FPI to fixed acquisition-time operation have been reported [4, 5], but these frameworks ignore the limitations of currently available SPAD cameras, viz., their poor time-tagging performance compared to that of a single-pixel detector, and their pixel-to-pixel variations of quantum efficiency and dark-count rate [2, 3]. Therefore, until now, a photon-efficient reconstruction algorithm for SPAD-camera imaging and an experimental validation of its performance are still missing.

Here we propose a photon-efficient computational imaging algorithm that can deal with the aforementioned limitations that SPAD cameras suffer. We use a SPAD-camera prototype to experimentally demonstrate accurate 3D structure and reflectivity imaging of natural scenes obtained from ∼1 detected signal photon per pixel. Because the SPAD-camera based imager provides a much higher frame-rate than raster-scanning setup, our results demonstrate low light-level imaging that can for the first time achieve both high photon efficiency and high-speed data acquisition.

Experiment. Our experimental setup is illustrated in Fig. 1. The illumination source was a pulsed laser diode whose original output-pulse duration was increased to a full width at half maximum of ∼2.5 ns for optimum depth-imaging accuracy, given the sub-ns (∼390 ps) time-tagging resolution of the SPAD-camera prototype [3]. A diffuse plate spatially spread the laser pulses to flood illuminate the scene of interest. An incandescent lamp injected unwanted background light into the camera. A standard Canon FL-series photographic lens focused the signal plus background light on the SPAD-camera’s detector array. Each photon detection from the array was time tagged relative to the time of the most recently transmitted laser pulse and recorded. The SPAD array [3] consists of 32 × 32 pixels of fully independent Si single-photon avalanche diodes and CMOS-based electronic circuitry that includes a time-to-digital converter for each SPAD detector. The array has a ∼390 ps time resolution set by its internal clock rate. To extend the region that could be imaged and increase the number of pixels, we used multiple image scans to form a larger-size composite image. In particular, we mounted the SPAD array on a feedback-controlled, two-axis motorized translation stage, to produce images with 384 × 384 pixels.

Algorithm. In the low-flux regime, wherein there are very few detections and many of them are extraneous background-light detections or dark counts, an algorithm that relies solely on the conventional pixelwise photode-
Fig. 1. Experimental set-up. A repetitively-pulsed laser flood-illuminates the scene of interest. Laser light reflected from the scene plus background light is detected by a SPAD camera. Photon detections at each pixel are time tagged relative to the most recently transmitted pulse and recorded. The raw photon-detection data is processed on a standard laptop computer to recover the scene’s 3D structure and reflectivity. The inserted photo on the top shows the hardware of the SPAD camera prototype.

tection statistics [6] has very limited robustness. To solve this problem, our reconstruction algorithm first exploits the scene’s structural information in both transverse and longitudinal domains to suppress extraneous detections, and then it optimizes between two constraints for a given set of censored measurements: (i) the image should yield a scene that is sparse and smooth; (ii) the image should resemble a scene expected from raw single-photon measurements with Poisson statistics. The algorithm consists of three steps.  

**Step 1:** Natural scenes have pixel reflectivities that tend to be similar to the reflectivities of their nearest neighbors. This transverse-smoothness constraint is enforced in our algorithm by using a total-variation (TV) norm [7] penalty on the log-likelihood of our reflectivity image.  

**Step 2:** Natural scenes have a finite number of reflectors that are clustered in depth. This longitudinal-sparsity constraint is enforced in our algorithm by first solving a sparse deconvolution problem from the coarsely time-binned photon detection data to obtain the small number of representative scene depths. We then delete photon detections that are more than a pulsewidth away from all of the estimated depth clusters.  

**Step 3:** Similar to what was done in Step 1 for reflectivity estimation, we impose a TV-norm spatial-smoothness penalty on the log-likelihood of our depth image using the censored (non-extraneous) photon detections from Step 2.

**Results.** Figure 2 shows experimental results of 3D structure and reflectivity reconstructions for a scene comprised of a mannequin and sunflower when, averaged over the scene, there was \( \sim 1 \) signal photon detected per pixel and \( \sim 1 \) extraneous (background-light plus dark-count) detection per pixel. We compare our proposed method with the baseline pixelwise imaging method that uses filtered histograms [6]. Although the filtered-histogram reflectivity image (Fig. 2a) is of reasonable quality, it is clearly inferior to ours (Fig. 2b), which compares quite well to the ground-truth reflectivity image (Fig. 2c) obtained from pixelwise processing of high-flux measurements. More importantly, the filtered-histogram depth image (Fig. 2d) is too noisy to show any useful depth features, whereas our array-specific method (Fig. 2e) succeeds in capturing accurate depth information at low flux. The accuracy of depth estimation was quantified by comparing our framework’s result with the ground-truth depth image (Fig. 2f) obtained from pixelwise processing of high-flux measurements. We found that our method successfully recovers the scene’s depth structure with good resolution, while the filtered-histogram fails to do so (Fig. 2g,h). In particular, despite our SPAD camera’s \( \sim 390 \) ps time-bin duration [3]—which corresponds to \( \sim 6 \) cm depth resolution—our method recovers depth with a sub-bin-duration mean absolute error of \( \sim 2 \) cm. Thus it significantly outperforms existing computational imaging methods for low-flux operation [4–6].
Fig. 2. **a, b, d, e,** Reflectivity and depth images, obtained from an average of \(\sim 1\) detected signal photon per pixel, using the pixelwise filtered histogram [6] and our proposed framework. **c, f,** Ground-truth reflectivity and depth images obtained from detecting 550 photons per pixel. **g, h,** Depth-error maps obtained by taking the absolute difference between estimated depth and ground-truth depth, where background is masked in order to show the object of interest – mannequin+sunflower.

**Conclusion.** We have proposed and demonstrated a SPAD-camera imaging framework that generates highly-accurate images of a scene’s 3D structure and reflectivity from \(\sim 1\) detected signal photon per pixel in the presence of extraneous detections, occurring at roughly this same rate, from background light and dark counts. By explicitly modeling the single-photon observations from the SPAD camera’s detector array, our framework dramatically improves reconstruction accuracy in this low-flux regime as compared to what is achieved with existing methods. Because our framework employs a SPAD camera for highly photon-efficient imaging, it opens up new ways to image 3D structure and reflectivity on very short time scales while requiring very few photon detections. It could therefore find widespread use in applications that require fast and accurate imaging using extremely small amounts of light, such as remote terrestrial mapping, seismic imaging, and fluorescence lifetime imaging.

**References**

1. A. Kirmani, *et al.*, Science **343**, 58–61 (2014).
2. J. Richardson, L. Grant, and R. K. Henderson, IEEE Photonics Tech. Lett. **21**, 1020–1022 (2009).
3. F. Villa, *et al.*, IEEE J. Sel. Top. Quantum Electron. **20**, 3804810 (2014).
4. Y. Altmann, *et al.*, arXiv:1507.02511 [Stat.ap] (2015).
5. D. Shin, A. Kirmani, V. K. Goyal, and J. H. Shapiro, IEEE Trans. Comput. Imaging **1**, 112–125 (2015).
6. G. S. Buller, and A. M. Wallace, IEEE J. Sel. Top. Quantum Electron. **13**, 1006–1015 (2007).
7. A. Chambolle, *et al.*, “An introduction to total variation for image analysis,” in M. Fornasier, ed., *Theoretical Foundations and Numerical Methods for Sparse Recovery*, (Walter de Gruyter, Berlin, 2010), pp. 263–340.