Lateral-resolution enhancement of low-photon 3D-LiDAR by compressive sensing

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ABSTRACT

ONERA – The French Aerospace Lab – develops new concepts of 3D-LiDAR imaging systems including new sensor technologies and data processing. Here, we present a more efficient strategy than existing solutions to numerically enhance the lateral resolution of low photon 3D-LiDAR operating in Geiger mode. Our pipeline makes it possible to reconstruct 3D-images with an unprecedented lateral-resolution, simultaneously at low photon count and Hertz level framerates. It is applied on simulated GmAPD 3D-LiDAR signals. Signals acquired using this category of sensors are unsuitable for direct applications of Compressive Sensing algorithms. Our contribution focuses on a more efficient strategy for waveform denoising and reconstruction. For each pixel, we reconstruct sub-pixels by using a Compressive Sensing approach. Compressive Sensing has already been used for single-photon applications with single-pixel cameras. In our pipeline, we extend this method to focal plane arrays in Geiger-mode. This process can be summarized as a set of signal processing techniques to enhance the incoming signal and to improve the Compressive Sensing reconstruction. Our goal is to recover a complete noise-free waveform. We distinguish two main parts: a reconstruction part which compensates the low dynamic range of the signal induced by the Geiger mode; a denoising part which uses a new denoising strategy based on statistical comparisons. This pipeline can be parallelized on GPU, as each pixel in the focal plane array is independent from the others. In this paper, we will detail the pipeline and then demonstrate its applicability on realistic simulated data.

Keywords: Compressive Sensing, 3D-LiDAR, Enhanced lateral-resolution, Low-photon count imaging, Signal processing, Focal plane arrays, Geiger mode Avalanche Photo-Diode, GmAPD

1. INTRODUCTION

Single-photon cameras are increasingly being used in 3D-LiDAR sensing systems, especially in low Size Weight and Power (SWaP) systems. Here we focus on systems using Geiger-mode Avalanche Photodiode (GmAPD) sensors. These sensors are highly sensitive,[1] capable of statistically detecting fractional photons return levels. This, coupled with centimeter depth-resolution provides a competitive edge against "classical" linear systems. This is especially true in long range ($>$ 10 km) remote sensing and surveillance applications. However, SWIR-GmAPD sensors are limited to a few large pixels (up to 128×32 pixels),[2] which may result in insufficient resolution. Increasing the pixel count at the sensor level might pose its own problems, namely the size of the image plane and light gathering capabilities. Increasing lateral-resolution could be achieved using Compressive Sensing (CS) algorithm.[3] In this work, we reconstruct the 3D-images using CS considering each pixel in the Focal Plane Array (FPA) as a single-pixel detector. We use a Digital Micro-mirror Device (DMD) to modulate the incoming light onto the FPA in a binary basis used in CS. Note that GmAPD sensors can only detect the first photon without information on photon count. Those properties could degrade the reconstructed-image using CS. To tackle this issue, we also developed signal processing methods should be applied upstream to correct them.

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2. PIPELINE GENERAL CONCEPT

2.1 Motivation and principle

The main idea of the proposed pipeline is to used photon-counting FPA instead of single-pixel camera to achieved LiDAR system with higher resolution at long-range. Using CS, the framerate could be kept low while increasing lateral-resolution. With the same purpose, we which to keep signal-level rather high (> 0.1 photon in average).[4] Considering signal-level above superior at 0.1 photon in average, imply the introduction of dead-time effect, sometime referred as pile-up.[5,6] Indeed, as only the first backscattered signal could be acquired due to dead-time, all others are lost. Dead-time effect introduced unwanted temporal-correlation, which limit the accuracy of CS reconstruction.[7]

For instance, the temporal resolution is sufficient, with CS we which to increased only the lateral-resolution. Therefore, for each temporal bin we increase lateral-resolution with CS. Thus, we suppose that each bin is independent of previous bin if the impulse is short enough. Such that, for a given pattern, CS measurement variation depend essentially of cross-section. These hypotheses are not meet when dead-time effect occurs. This will introduce unwanted reconstruction artifacts using CS to increase resolution.

SNR can be low. Moreover, using CS to reconstruct an image in bin with only noise isn't efficient computationally. We could take advantage of the LiDAR system specification. Indeed, considering the fact that state-of-the-art GmAPD sensor[2] as an acquisition framerate higher than the pulse frequency of state-of-the-art LiDAR ruggedized for low SWaP application.[8] Denoising signal could be done by comparing statistically useful-frame (with pulse) and noise-frame (without pulse) acquired between each useful-frame. We summarize our method in a pipeline as shown in fig. 1, where different step corresponds to (i) compressed acquisition using DMD, (ii) return-times histogram following TSCPC approach, (iii.a) waveform dead-time effect correction, (iii.b) support estimation with statistical test using additional noise frame, (iv) merge step (iii) by multiplication, (v) recover an image for each bin using CS.

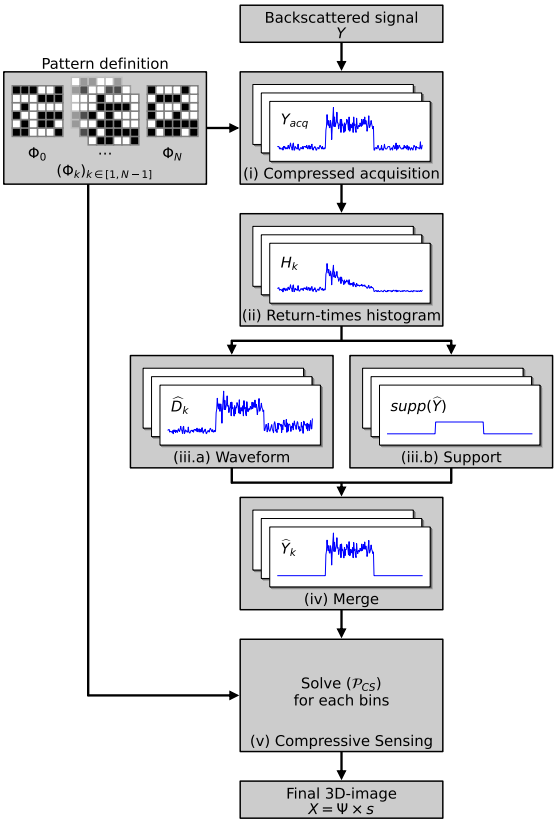


Figure 1: Illustration of a pipeline increasing lateral resolution of 3D-LiDAR using CS

2.2 Compressive Sensing

CS is a signal processing technique that compresses the signal during the acquisition in specific basis (collection of patterns) and then uses a priori knowledge to reconstruct the acquired compressed information.[9–11] CS algorithms use an a priori on the sparsity of the scene in a certain basis (which may be unknown) and the incoherence between this basis and a specific measurement basis which is an incomplete linear system. That knowledge enables CS algorithm to reconstruct exactly the image by solving L1 optimization problem, using fewer measurements than a "classical" acquisition.

$$\hat{s} = \min_{s \in \mathbb{R}^N} ||s||_1, \text{ s.t. } ||Y - \Phi\Psi s||_2^2 = 0$$

Where the image to reconstruct is $X = \Psi s \in \mathbb{R}^N$, $\Psi \in \mathbb{R}^{N \times N}$ is the basis that promote sparsity, $\Phi \in \mathbb{R}^{M \times N}$ is the linear measurement process and $Y \in \mathbb{R}^M$ is the resulting measurement with $M << N$.

2.3 Dead-time effect

Dead-time effect occur if the backscattered light generates a signal with multiple echoes. The coefficient of a pattern is defined as the signal acquired for a given (discrete) time and pattern. Consider two acquisitions with two different patterns but identical cross-section. In this case, their pattern coefficients must be equal, regardless of the detections made at previous times. This is because the coefficient of a pattern corresponds to a measurement in the CS framework, and getting the measurement wrong necessarily introduces errors in the reconstruction. These errors manifest themselves mainly as artifacts on the reconstructed point cloud. Thus, if this condition is not met, the estimation of the pattern coefficients may be erroneous, making the reconstruction of the 3D image by CS incorrect.
fig. 2 shows the temporal-correlations. Two patterns are selected. Pattern (Φ_{k_1}) hides only one object. Both objects are visible with pattern (Φ_{k_2}). In the first case (Φ_{k_1}), the signal peaks twice as high as in the second at the time corresponding to the triangle position. The signal recovered for (Φ_{k_2}) should have an identical peak for the "triangle" object because they have an identical effective cross section. This illustrates the stacking effect on the temporal signal with the pattern selection induced by the camera's dead time. The same effect occurs for a slope or any combination of targets producing multiple echoes in the recovered signal.

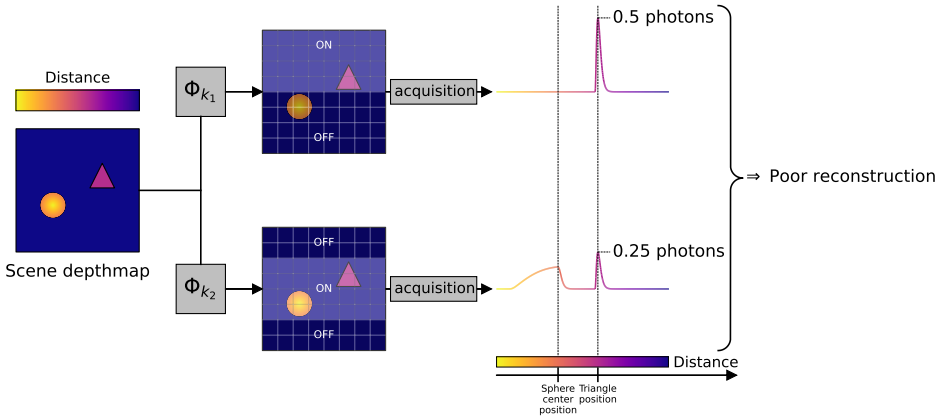


Figure 2: Illustration of time dependency

Recent advanced on the field are focused on model involved calculation as Bayesian inference[12] or Markovian Chain model[13] to tackle this issue. While those approaches give very precise results, they could be too much computationally intensive (from 8s to few hours[13]). Indeed, as we deal with CS for each frame reconstruction the method should be applied for each pattern in each pixel. Thus, similarly to[7] we choose to use simpler and faster algorithm as the correction proposed by Coates.[5,6]

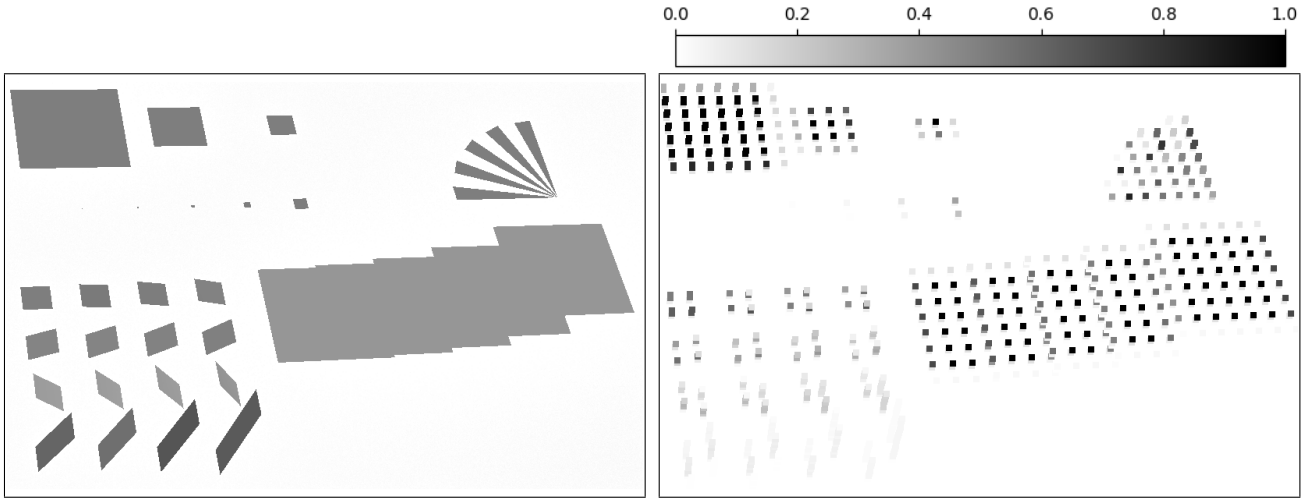
2.4 Denoising strategy

The denoising strategy could be summarize as acquire additional frame of noise between each useful-frame with a concomitant laser pulse, then compare each histogram-bin statistically. The comparison is made for each bin considering as two statistical population the histogram-bin for a given pattern with and without concomitant laser pulse. To test if both populations have the same distribution, we use the non-parametric Mann-Whitney U-test.[14] This allows us to determine whether or not the bin contain a backscattered signal. Determine each bin that contain a backscattered signal give us an estimation of the function support as shown in Fig. 1. After correcting the dead-time effect and estimate the function support we merge both simply by a multiplication before applying CS algorithm.

3. RESULT AND DISCUSSION

3.1 Data

We validate our proof-of-concept, using 3D-LiDAR acquisitions under realistic daylight conditions simulated by MATLIS software.[15,16] The 3D scene was designed to illustrate the improvement brought by the method (fig. 3).

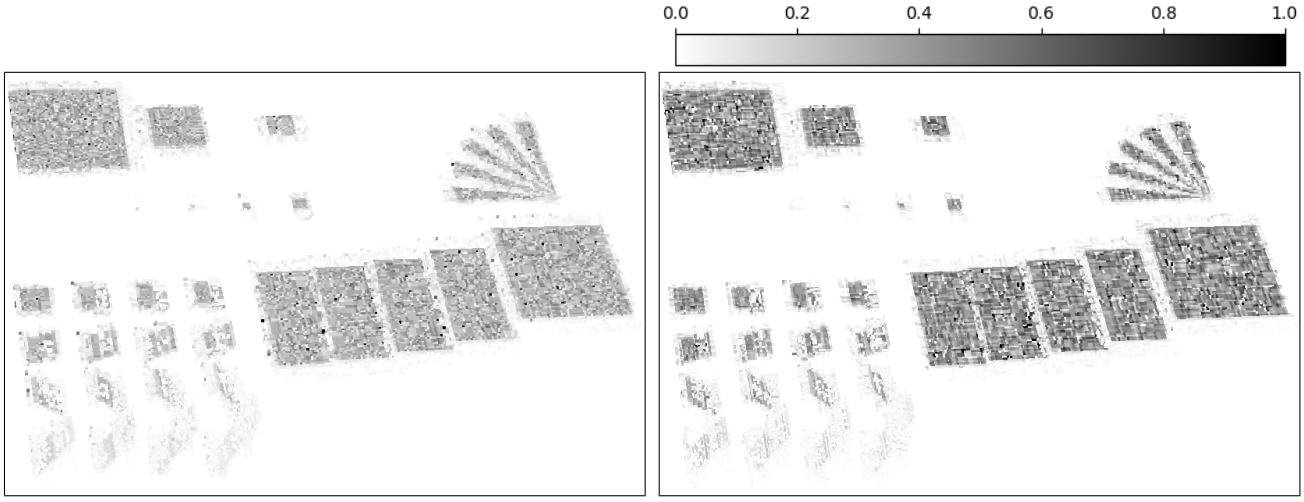


(a) (b)

Figure 3: (a) 3D scene with various features as high frequency, different size and inclination, all materials are considered as 10% Lambertian; (b) Simulated LiDAR acquisition from the 3D scene after removing noise. Gray scale in (b) is the normalized intensity.

3.2 Result

As shown in Figure 4, the pipeline recovers many scene details from the raw data due to the increased number of points. Reconstruction artifacts (e.g., holes, noise), resulting from solving the CS optimization problem, can be noticed. Higher spatial frequencies (ray target) and flat surfaces with a cross section smaller than the size of a projected DMD pixel are not recovered (synthetic scene). Our method has clear advantages for detail recovery by reconstructing better defined edges as in cases like in squares and slope (figs. 4a and 4b). Another advantage concerns the reconstruction of objects with high spatial frequency (Siemens star). The lateral resolution is increased by a factor of 8 in each lateral direction, the depth resolution remains unchanged. Moreover, using only half of the total number of measurements doesn't lower significantly the reconstruction quality.



(a) (b)

Figure 4: 3D reconstruction from a pipeline using the Haar basis as sparsifying basis and the Hadamard transform as measurement process with (a) all patterns and (b) only half. The gray scale represents the normalized intensity on both images. Gate start at 13km from the sensor.

4. CONCLUSION

We have described in this paper a comprehensive pipeline to increase the lateral resolution of 3D-LiDAR GmAPD systems using compressive sensing (CS). Our pipeline takes into account the nature of the signal by using a statistical approach to denoise, which is novel for this application, and estimate a corrected waveform before solving the CS optimization problem. The feasibility of our method is demonstrated numerically on simulated data. In our case, the lateral resolution is improved by 64 times while preserving the depth resolution and minimizing artifacts. This pipeline therefore appears as particularly appealing for very long-range daylight observation. We have validated it on static targets, but future work will focus on the reconstruction of moving targets by evaluating the use of pattern matching.

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