

What's Next in ToF Imaging: Passive Operation, One-bit Quantization, and Spatiotemporal Superresolution

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Abstract: Time-of-Flight (ToF) imaging is an active 3D imaging technique that leverages the fact that time of arrivals of photons can be used to encode the 3D geometry of a scene. Decoding distances from photon arrivals requires time-resolved pixels, known as ToF pixels. ToF imaging is nowadays a mature technology and a number of design choices have become standard, be due to legacy from initial designs, coherence with conventional imaging, or simplicity. In this talk we draw attention to three typically unspoken design tradeoffs and unveil their potential to refine the performance of future ToF imaging systems. These are: 1) passive operation, 2) bit depth, and 3) demodulation schemes.

Keywords: Time-of-Flight, one-bit quantization, passive ToF, compressive sensing, superresolution

1. Introduction

Time-of-Flight (ToF) imaging is an active 3D imaging technique that leverages the fact that photons can be used to encode the 3D geometry of the scene in their arrival times, thanks to the constancy of the speed of light in a given medium. The scene is flood-illuminated with modulated light and the reflected light is projected onto an array of demodulating pixels by means of a lens. These pixels, known as ToF pixels, are necessarily endowed with time-resolving capabilities. In other words, the measured value depends on when the photon arrivals occur, by virtue of a time-domain control signal. ToF imaging is nowadays a mature technology and a number of design choices have become standard, be due to legacy from initial designs, coherence with conventional imaging, or simplicity. In this talk we focus on three often-neglected design tradeoffs and unveil their potential to further improve the performance of state-of-the-art ToF imaging systems [1].

2. Collaboration instead of competition

A key opportunity that has remained largely ignored to date is the exploitation of existing sources of modulated light. With the increasing presence of LEDs and VCSELs as light sources in illumination systems, novel devices often exploit the modulation bandwidth of these emitters to provide simultaneous lighting and communications. We will show how such opportunity illuminators can be leveraged to obtain “passive” ToF imaging. Recent works have shown the feasibility of this idea, demonstrating depth estimation without photon emission, leveraging existing VLC and LiFi modules [2].

3. One-bit ToF imaging

A second design parameter that is often overseen is the bit depth of the measurements. Typically, uniform quantization at constant bit depth is assumed. The number of bits is then chosen to obtain the resolution dictated by the best-case noise floor of the measurements. This is suboptimal, in general. In modern systems acquiring multiple frames of raw data for generating each depth image, correlations between consecutive measurements can be exploited to implement low-bit quantization schemes. The band-limited nature of real cross-correlation functions allows for one-bit ToF imaging. This idea was first introduced in [3], where multi-path ToF imaging was demonstrated using one-bit ToF raw data obtained using well-understood noise-shaping techniques.

4. Demodulation schemes for spatiotemporal superresolution

The third often-neglected design possibility is the engineering of optimal demodulation functions, so that the maximum amount of information from the scene response function (SRF) is captured with the minimal number of measurements. This allows for minimizing the number of measurements (thus, maximizing the frame rate) required to obtain a desired depth resolution or, complementarily, aiming for temporal superresolution exploiting compressive sensing (CS) techniques [4]. From the CS perspective, the challenge is to obtain a sensing matrix with the lowest possible inter-column coherence. In combination with custom ToF array designs that allow single-shot acquisition of raw data, spatiotemporal superresolution becomes feasible by leveraging both temporal sparsity of the SRF, and local spatial correlations [5].

5. Conclusion

Despite current ToF imaging techniques are the result of a process of continuous improvement over the last two decades, exciting research avenues remain largely unexplored and hold promise for further improvements in terms of power consumption, depth resolution, and data flow.

References

- [1] M. Heredia Conde, "Compressive Sensing for the Photonic Mixer Device," Springer, ISBN: 978-3-658-18056-0, April 2017, DOI: [10.1007/978-3-658-18057-7](https://doi.org/10.1007/978-3-658-18057-7).
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- [4] A. Lopez Paredes, M. Heredia Conde and O. Loffeld, "CS-ToF Sensing by Means of Greedy Bi-lateral Fusion and Near-to-optimal Low-density Codes," in *30th European Signal Processing Conference (EUSIPCO)*, pp. 1996-2000, 2022.
- [5] A. Lopez Paredes, M. Heredia Conde and O. Loffeld, "Sparsity-aware 3D ToF Sensing". TechRxiv, 22-Feb-2022, DOI: [10.36227/techrxiv.19161749.v1](https://doi.org/10.36227/techrxiv.19161749.v1).

Annex 1: Slides on Passive ToF Imaging

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Passive-ToF Imaging

3D ToF Imaging without emitting a single photon

- Passive ToF imaging: 3D reconstruction by processing reflections from non-cooperative sources of illumination present in the scene, such as VLC/LiFi sources.
- Two co-located receivers: a photodiode and the ToF camera.

Problems	Solution
High-power consumption	Visible Light Communication infrastructure
Background light disturbance	Ubiquitous presence of modulated light signals
Temperature effects	

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Bistatic Sensing Model

Definitions

- Reference cross-correlation function $\varphi_{\mathbb{R}^N}$
- $\mathcal{D}_k: \mathbb{R}^N \rightarrow \mathbb{R}^K$ Downsampling operator
- $[D_k(\vec{V})]_j := V_{1+(j-1)k}$
- $\mathcal{S}_c: \mathbb{R}^N \rightarrow \mathbb{R}^N$ Shifting operator
- $[S_c(\vec{V})]_k := V_{1-c}$

Using the operators defined above, we model the measurement \vec{Y}^M and candidate (test) $\vec{Y}^T(\Delta\tau)$ vectors from real data, \vec{y}^R .

$$\vec{Y}^M = \mathcal{D}_k(\mathcal{S}_c(\vec{V}^R)) \quad \vec{Y}^T \in \mathbb{R}^K \quad l_c = N \tau / T \quad R = N / K$$

$$\vec{Y}^T(\Delta\tau) = \mathcal{D}_k(\mathcal{S}_{\Delta\tau}(\vec{y}^R)) \quad l_{\Delta\tau} = N \Delta\tau / T \quad R = N / K$$

Bistatic Geometry

- The estimated depth is given by $d = \frac{c}{2} \arg \max_{\Delta\tau} (\vec{Y}^T(\Delta\tau), \vec{Y}^M)$
- Feasible target locations: 3D ellipsoid $d = d_{RT} + d_{RT}$
- 3D location of the target is written as $\vec{r} = \vec{r} + d_{RT} \vec{d}_{RT}$
- The resulting camera-to-target depth in the bistatic geometry setting is given by, $d_{RT} = \frac{d_{RT}^2 - d^2}{2[(C_c u_{Tx} + C_c u_{ToF} + C_c u_{Rx}) - d]}$

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From Active to Passive ToF Imaging

- A bistatic geometry makes use of two sensing paths:
 - Direct path:** Link established between a reference photodiode and the light source.
 - Indirect path:** Indirect channel constituted via reflection on the targets to the ToF camera.
- Our passive sensing pipeline requires the use of an external demodulation signal for synchronizing the ToF camera.

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Sampling Approaches

- Aim: reduction of the number of measurements by exploiting different sampling approaches.
 - Uniform sampling (US):** The signal is sampled at regular time shift intervals.
 - Random Sampling (RS):** The samples are randomly distributed over the sampling domain.
 - Sparse-ruler Sampling (SRS):** Few sampling points on a sparse grid that allows measuring all integer value between zero and the total grid size. We exploit a sparse ruler of type **Wichmann W(2,5)**

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Paradigm Shift

- Introduction of VLC into the sensing game**
 - Recent technology shift in lighting: from incandescence lamps to light-emitting diodes (LEDs). This is a key enabler for an emerging communication technology.
- Intelligent lighting infrastructure**
 - Provide multiple services, e.g., illumination and communication in indoor settings.
 - Opportunity illuminator for ToF imaging.
 - In recent years, VLC and ToF sensing have enjoyed unprecedented independent growth.
 - Idea: to **merge** the optical wireless communication technology and the ToF imaging technology.

A change of paradigm:
Optical wireless communication and ToF imaging systems **cooperate** instead of **competing**.

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Experimental Setup

- Demonstrates a different sensing principle, which emulates a correlation in optical domain.** This implies the use of **two parallel sensing arms** rather than a **single sensing arm** as in conventional methods.
- Our main goal is to exploit opportunity illuminators for achieving passive sensing:**
 - The position of emitter and receiver are known.
 - Pulsed-ToF imaging is demonstrated by making use of a matched filtering method.

- References:**
 - Passive ToF imaging by means of asynchronous transceivers. F. Ahmed, M. Heredia Conde and O. Loffeld, "Pseudo-Passive Indoor ToF Sensing exploiting Visible Light Communication Sources," 2021 IEEE SENSORS, 2021, pp. 1-4, DOI: 10.1109/SENSOR547087.2021.9639696.
 - Experimental setup and mathematical formulation for passive ToF imaging. F. Ahmed, M. Heredia Conde, P. Lopez, Martinez, T. Kerstein and B. Buxbaum, "Pseudo-Passive Time-of-Flight Imaging: Simultaneous Illumination, Communication, and 3D Sensing," in IEEE Sensors Journal, 2022, DOI: 10.1109/JSEN.2022.3208085.

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Communications and Sensing Model

Communications Model

- Probing signal for ToF imaging and downlink user:** This may arise from a random sequence, $x(t)$, transmitted by the VLC communication source. LED impulse response is given as $h_{LED}(t) = -e^{-t/\tau}$
- $p_{TX}^{VLC}(t) = h_{LED}(t) * x(t)$
- Downlink communication**
 - Received optical signal in the time domain: $y(t) = p_{TX}^{VLC}(t) * h_{LOS}(t) + n(t)$
 - $h_{LOS}(t) = \delta(t - \Delta t)$ is the line-of-sight (LoS) response.

Sensing Model

- $r(t) = (p_{TX}^{VLC}(t) * h_{NLOS})(t)$ reflected signal. This is defined as the interaction between the probing signal and the scene response function (SRF), $h_{NLOS}(t) = \Gamma \delta(t - \tau)$, $\tau = 2d/c$.
- $zm(t) = (y_{NLOS} \otimes r)(t)$ is the measurement signal. Sampling this signal yields digital samples.
- Demodulation control signal (DCS):**
 - Obtained applying a thresholding operator, \mathfrak{Z} , to the optical signal received by the photodiode, $y_{NLOS}(t)$, which yields $y_{NLOS}^D(t) = \mathfrak{Z}(y_{NLOS}(t))$.

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Preliminary Results

Annex 2: Slides on One-bit ToF Imaging

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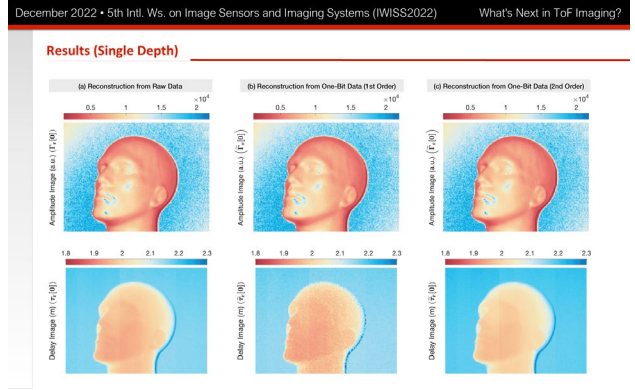
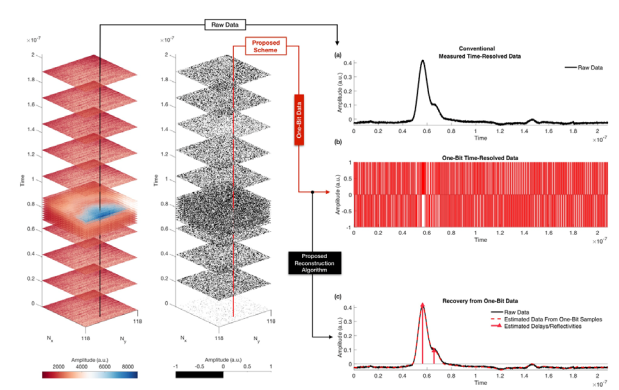
Technological Evolution

Lower Hardware Complexity

- Smaller size due to more efficient integration
- Lower power consumption
- Speed via faster operations
- Reduced cost

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Results (Single Depth)



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One-Bit Sensing Model (Bandlimited Functions)

- Our key idea is to replace the pixel architecture by a low-complexity, one-bit sampler.
- In conventional systems, Shannon-Nyquist approach is used. Sampling amounts to, $\mathcal{S}_{Sh}: f(t) \rightarrow f[n] = f(nT), n \in \mathbb{Z}, T > 0$.
- Our approach is based on $\mathcal{S}_{1B}: f(t) \rightarrow q[n] \in \{-1, 1\}$,

which is implementing

$$q[n] = \text{sgn}(u[n-1] + f[n])$$

$$u[n] = u[n-1] + f[n] - q[n]$$

One-Bit Sampling

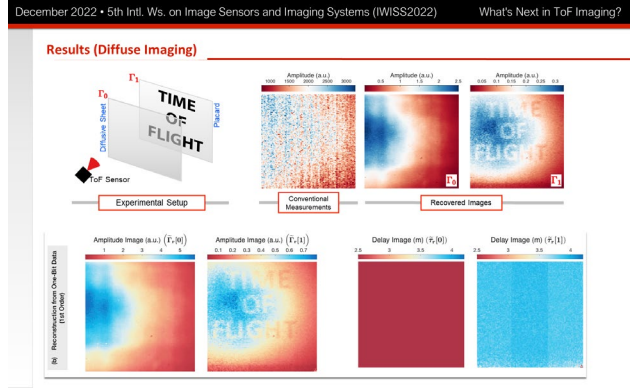
Recovery

$$\hat{f}(t) = \sum_{n=-\infty}^{\infty} q[n] \varphi\left(\frac{t}{\mu} - \frac{n}{\mu}\right)$$

Interpolation

Valid for Bandlimited Functions Only

Remarkably, the recovery simply follows an interpolation formula where μ denotes the oversampling factor and $\varphi(t)$ is a $\mu\Omega$ -bandlimited function.



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Multipath Imaging from One-Bit Data

- SRF $h_r(t, t') = \sum_{k=0}^{K-1} \Gamma_r[k] \delta(t - t' - \tau_r[k])$.
- One-Bit Measurements in Fourier Domain, $\hat{Q}_{r,\phi}(\omega) = \hat{Q}_r(\omega) \sum_{k=0}^{K-1} \Gamma_r[k] e^{-j\omega\tau_r[k]} - \hat{D}_r(\omega) (1 - e^{-j\omega\mu})$.
- We can estimate ϕ by using a calibration experiment, $\hat{Q}_{r,\phi}(\omega) = \hat{Q}_r(\omega)$, $\omega_0 = 2\pi/N, |m| \in M_0$.
- We now isolate the unknown SRF using, $\hat{\Gamma}_r(\omega) = \frac{\hat{Q}_r(\omega)}{\hat{Q}_{r,\phi}(\omega)} \approx \sum_{k=0}^{K-1} \Gamma_r[k] e^{-j\omega\tau_r[k]}, |m| \in M_0$.

Sum-of-Sines

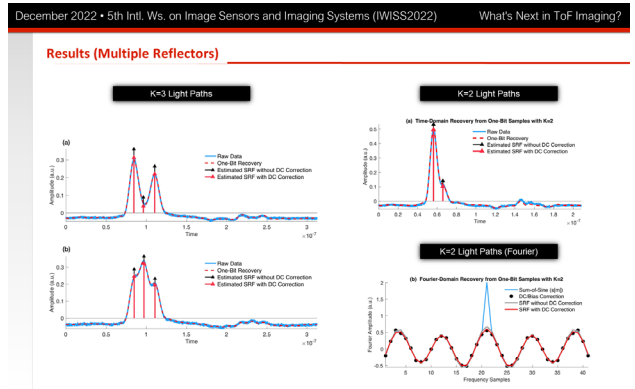
Algorithmic Steps

- Given:
 - One-bit samples $q_r[n]$ for a given pixel r .
 - One-bit samples of calibrated pulse $q_{c,\phi}[n]$.
- Perform deconvolution in Fourier domain.
 - Choose bandwidth M_0 of pulse $q_{c,\phi}[n]$.
 - Compute, $\hat{\Gamma}_r(\omega) = \frac{\hat{Q}_r(\omega)}{\hat{Q}_{c,\phi}(\omega)}, |m| \in M_0$.
- Solve sine-fitting problem. $\min_{\Gamma_r} \sum_{(m_1, m_2) \in M_0} |\hat{\Gamma}_r(\omega) - \sum_{k=0}^{K-1} \Gamma_r[k] e^{-j\omega\tau_r[k]}|^2$.

Solved using Matrix Pencil Method, of BhandarkR (ICASSP, 2013).

Related works: Li & Sponed (2000) • Vetterli et al. (2002) • Candes & Granda (2014).

BhandarkR, ICASSP 2013
BhandarkR, IEEE SPMag 2015



Annex 3: Slides on Spatiotemporal Superresolution

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CS-ToF imaging

- A practical Compressive Sensing (CS) scheme to increase depth and angular ranges, and to improve the depth resolution.
- Construction of the sensing matrices:
 - Optimization of coherence:
 - Construction by columns via Gradient Combinatorial search.
 - Introduction of near-to-optimal shifts between rows.
 - Exploiting two-tap (PMD) architecture.
- Sparsity-aware signal recovery:
 - Temporal super-resolution schemes:
 - Sliced OMP.
 - Greedy bilateral fusion.
- Current line of research:
 - Spatiotemporal super-resolution.
 - Spatial super-resolution framework leveraging sub-pixel intensity maps.
 - Temporal super-resolution considering theoretical sensing matrices.

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CS-ToF imaging: Sparsity-aware Signal Recovery

- Sliced OMP:
 - A preliminary set of N_c measurements, representing disjoint depth sub-domains, is used to refine the signal support.
 - This helps to disregard large empty areas, improve the aspect ratio of the sensing matrices, and reduce the computational cost.
 - The depth and amplitude are recovered in the refined spatial domain via OMP using N_r additional measurements.
- The output of this research was presented in IEEE SENSORS 2021.
 - The sensing matrices used were (0,1)-binary random matrices and Scrambled Hadamard Ensembles (SHEs) with (0,1)-re-scaling.
 - The scheme was validated by performing numerical simulations using Ground Truth (GT) from disparity and intensity maps of Middlebury datasets 2003 and 2005.

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CS-ToF imaging: ToF Sensing Scheme

- Scope of our research:
 - Development of a 3D ToF camera capable of covering very-wide areas and long ranges at a relatively low computational cost.
- Current limitations of ToF cameras:
 - Lateral range limited by the Field of View of the optical system.
 - Introduction of motion artifacts in unsteady scenarios.
- Proposed solutions:
 - Mechanical rotation around the vertical axis.
 - Drastic reduction of the exposure time.
- Current status:
 - Final phase of the construction and assembling of the prototype.

Reference: A Lopez-Paredes, M. Heredia-Cardo, and O. Luffel, "Effective Very-wide area 3D ToF Sensing," in 2021 IEEE SENSORS, 2021, pp. 1-4. DOI: 10.1109/SENSOR547087.2021.9636985.

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CS-ToF imaging: Sparsity-aware Signal Recovery

- Greedy bilateral fusion:
 - We aim to improve the recovery performance for signals with low SNR during the retrieval process, by considering the intensity information from adjacent pixels.
 - The output of this research was presented in EUSIPCO 2022.
- Algorithmic Steps (for k^{th} pixel, s^{th} iteration):
 - Step 0: Initialization of support $\beta^{(k,0)} = \emptyset$, estimate of $\hat{x}^{(k,0)} = \vec{0}$, and residual $\tilde{r}^{(k,0)} = \tilde{y}^{(k)}$.
 - Step 1: Generation of discrete probability function $g_{j^{(k,s)}}^{(k,s)} = \frac{(\tilde{y}^{(k)})^2 \delta_{j^{(k,s)}-1}}{\|\tilde{y}^{(k)}\|_1}$.
 - Step 2: Estimation of the forbidden support $\Gamma^{(k,s)}$, and posterior thresholding $\hat{g}_{j^{(k,s)}}^{(k,s)} \leftarrow 0$.
 - Step 3: Re-calculation of $\hat{g}_{j^{(k,s)}}^{(k,s)}$ using bilateral filtering $\hat{g}_{j^{(k,s)}}^{(k,s)} = \frac{\sum_{L \in \mathcal{N}(j^{(k,s)})} W(L, j^{(k,s)}) \tilde{y}^{(k)}(L)}{\sum_{L \in \mathcal{N}(j^{(k,s)})} W(L, j^{(k,s)})}$.
 - Step 4: Recovery of the target location $J_{\text{max}} = \arg \max_{j^{(k,s)}} (\hat{g}_{j^{(k,s)}}^{(k,s)})$.
 - Step 5: Update of support $\beta^{(k,s+1)} = \beta^{(k,s)} \cup J_{\text{max}}$, estimate of $\hat{x}^{(k,s+1)} = A_{\beta^{(k,s+1)}}^{\dagger} \tilde{y}^{(k,s)}$ and residual $\tilde{r}^{(k,s+1)} = \tilde{y}^{(k,s)} - A_{\beta^{(k,s+1)}} \hat{x}^{(k,s+1)}$.
- Note: In the bilateral filter weights, the L_2 -norm of the residual of the measurement vector for each pixel is used to approximate intensity values: $\tilde{y}^{(k,s)} = \|\tilde{r}^{(k,s)}\|_2$.

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CS-ToF imaging: Construction of the Sensing Matrices

- Gradient Combinatorial approach.
 - The number of columns of the theoretical sensing matrix A_0 is $n \leq n_{\text{max}}$, being n_{max} the maximum number of combinations without repetition of $n_{\text{dis}} \cdot n_{\text{ang}}$ non-zero elements in the m rows each column consists of.
 - The n columns are ordered in order to prevent any possible coincidence of rising and falling edges, which may lead to $\mu = 1$ in the real sensing matrix A .
- Introduction of near-to-optimal shifts
 - Each of the n elements of the grid can be discretized in up to n_{steps} yielding n_{samples} , which guarantees $\mu < 1$. This pushes the temporal (depth) resolution beyond the number of elements (columns) of A_0 .
 - Starting from A , we evaluate the distance between adjacent columns resulting from applying any possible on-grid shift in the row, and select the one which maximizes it.
- Exploiting the PMD-based two-tap architecture.
 - Considering no background illumination, we make use of the difference between both taps. This yields a further reduction of μ .

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CS-ToF imaging: Sparsity-aware Signal Recovery

- Greedy bilateral fusion:
 - Numerical simulations using GT from disparity and intensity maps of Middlebury dataset 2003.

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CS-ToF imaging: Construction of the Sensing Matrices

Summary of Sensing Matrices

References: A Lopez-Paredes, M. Heredia-Cardo, and O. Luffel, "CS-ToF imaging by means of greedy bilateral fusion and near-to-optimal low-density codes," in 2022 IEEE European Signal Processing Conference (EUSIPCO), 2022. A Lopez-Paredes, M. Heredia-Cardo, and O. Luffel, "Sparsity-aware 3D ToF Sensing," TechRxiv, Preprint https://doi.org/10.21203/rs.2022.10917154v1.

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CS-ToF imaging: Spatiotemporal Super-resolution for a Single-shot ToF 3D Camera

- Current lines of research:
 - Spatial single-frame super-resolution:
 - Low resolution of ToF cameras, especially the ones featuring macro-pixel architecture.
 - We exploit the arrangement of the sub-pixels within the macro-pixel to reliably reach sub-pixel resolution.
 - Spatial Super-resolution:
 - Determination of sub-pixel intensity maps.
 - Upscaling + bilateral filtering.
 - Temporal (depth) super-resolution:
 - The theoretical codes, the demodulation functions are built upon, may contain valuable information disregarded during the reconstruction process.
 - Coarse-to-fine greedy retrieval:
 - Preliminary screening step based on theoretical binary codes.
 - Signal recovery in the refined domain using the demodulation functions.
- Improvement of recovery performance especially under low-lighting conditions.