CS-based ToF Imaging

Alvaro Lopez Paredes, Miguel Heredia Conde, Otmar Loffeld

Center for Sensor Systems (ZESS), University of Siegen. Paul-Bonatz-Straße 9-11, 57076 Siegen, Germany
Corresponding author: alvaro.lparedes@uni-siegen.de

Abstract. *In this work, we explore several relevant concepts in Compressive Sensing (CS) theory. Firstly, we present two sensing schemes for the recovery of highly sparse signals named Sliced OMP and Zoned APEG. Then, we describe a number of construction methodologies for the sensing matrices which significantly reduce their coherence and density. The different procedures are validated through numerical simulations, and aim to ensure the successful reconstruction of the 3D scene under study with high probability.*

Keywords. Adaptive sensing, compressed sensing, 3D imaging, sparse recovery, Time-of-Flight.

University of Maribor Press

DOI https://doi.org/10.18690/um.3.2022.15
ISBN 978-961-286-658-7

1 CS-based ToF Imaging

1.1 Time-of-Flight Sensing Scheme and Signal Recovery Approaches

This study aims to investigate the 3D reconstruction of a scene from the measurements obtained by a pulse-based ToF camera. This yields the problem of recovering a very sparse echo signal for each ToF pixel. We exploit CS and sparsity-awareness techniques to perform this operation from few measurements and to achieve high depth resolution.

The first approach, whose structure is shown in Figure 1, is called Sliced Orthogonal Matching Pursuit (OMP) [1]. It is a non-adaptive procedure, since the construction of the sensing matrices does not require any previous knowledge of the signal to be recovered. It consists of the slicing of the spatial domain in a number of partitions in order to reduce the inter-column coherence (μ), i.e., to increase the dissimilarity between the columns of the sensing matrix. The signal is preliminarily localized between the partitions and, then, a greedy algorithm, such as OMP [2], is applied over the refined domain to retrieve the signal.

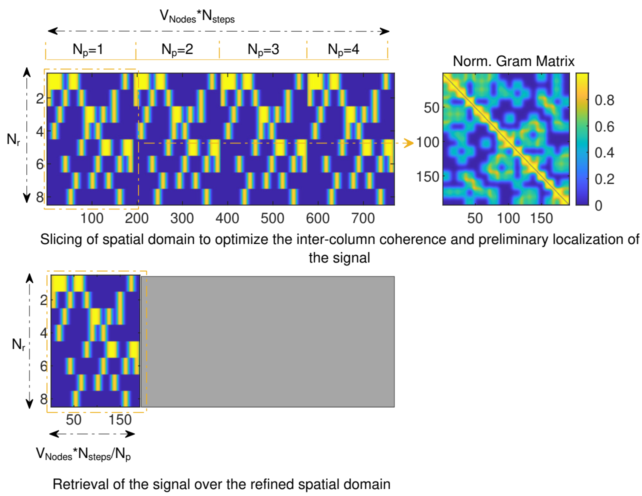

Figure 1. Sliced OMP

Zoned Adaptive Progressive Edge Growth (APEG) [6] extends the applicability of APEG [7] and paves the way to implement such a scheme in multi-aperture arrays [8]. The structure of Zoned APEG is presented in Figure 2. Zoned APEG builds the sensing matrix per rows by allocating a number of non-zero elements which accounts for the information on the signal support from the previous measurements, while it minimizes the coherence of the resulting matrix. When the process is complete, we can use the measurement vector and the sensing matrix generated to recover the signal. In our study, we use OMP for this purpose.

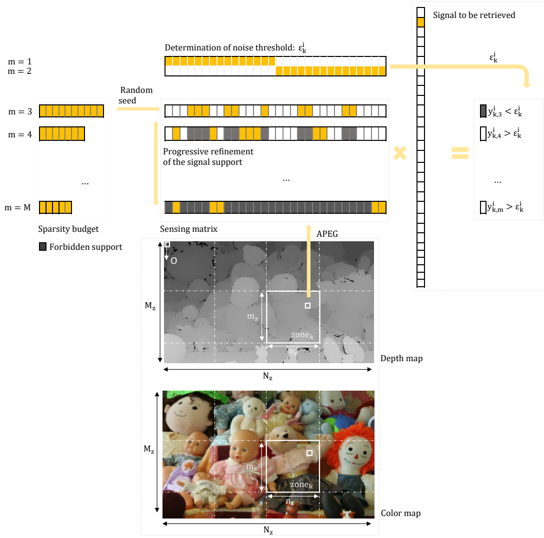

Figure 2. Zoned APEG over Middlebury dataset Dolls [3]–[5]

1.2 Sensing Matrices for Sliced OMP

Since the performance of Sliced OMP significantly depends on the selection of the type of sensing matrix, we perform an evaluation of different construction methodologies. Figure 3 summarizes the sensing matrices built via the different construction methodologies considered in [6], [9]–[11] and the corresponding normalized Gram matrices. The proposed techniques aim at minimizing their coherence and density. A low inter-column coherence helps ensuring unique reconstruction of sparse signals, whereas a low density reduces the memory footprint. The first four rows of Figure 3 present, from top to bottom, the sensing matrices from random binary (0,1)-codes, random binary (-1,1)-codes, (0,1)-Scrambled Hadamard Ensembles (SHEs) and (-1,1)-SHEs. The last four rows illustrate the sensing matrices generated using Low-Density Parity-Check (LDPC) codes generated via Progressive Edge Growth (PEG) [10], [11] and combinatorial approaches [6]. In addition, we present two extensions of these algorithms accounting for the non-instantaneous transitions from one element to another of the code which may lead to the coincidence of rising and falling edges and a subsequent degradation of the coherence. An evaluation of the performance of Sliced OMP using them as sensing matrices may be found in [1], [6].

Figure 4 shows the behaviour of the coherence with respect to the resolution of the grid and provides an estimation of the upper super-resolution limit, i.e., the minimum grid size which guarantees $\mu < 1$ [6].

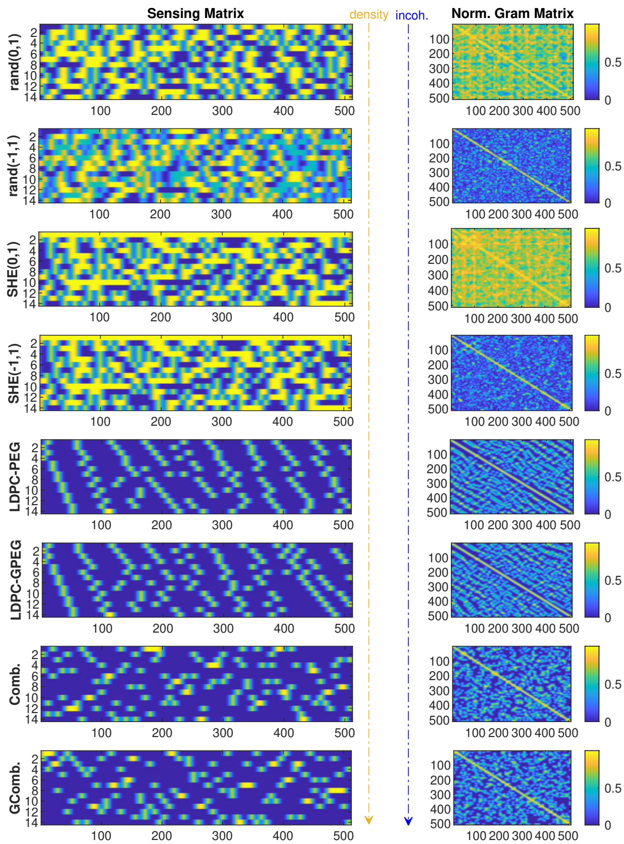

Figure 3. Sensing matrices for Sliced OMP

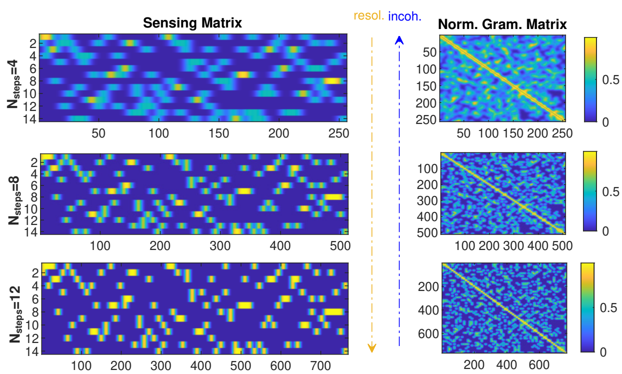

Figure 4. Upper limit for superresolution and discretization grid size

Acknowledgments

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 860370.

References

[1] A. Lopez Paredes, M. Heredia Conde, and O. Loffeld, "Effective very-wide-area 3D ToF sensing," in *2021 IEEE Sensors*, 2021, pp. 1–4. DOI: 10.1109/SENSORS47087.2021.9639585.

[2] Y. C. Pati, R. Rezaiifar, and P. S. Krishnaprasad, "Orthogonal matching pursuit: Recursive function approximation with applications to wavelet decomposition," in *Proceedings of 27th Asilomar Conference on Signals, Systems and Computers*, 1993, 40–44 vol.1. DOI: 10.1109/ACSSC.1993.342465.

[3] D. Scharstein and C. Pal, "Learning conditional random fields for stereo," in *2007 IEEE Conference on Computer Vision and Pattern Recognition*, 2007, pp. 1–8. DOI: 10.1109/CVPR.2007.383191.

[4] D. Scharstein and R. Szeliski, "High-accuracy stereo depth maps using structured light," in *2003 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2003. Proceedings.*, vol. 1, 2003, pp. I–I. DOI: 10.1109/CVPR.2003.1211354.

[5] H. Hirschmuller and D. Scharstein, "Evaluation of cost functions for stereo matching," in *2007 IEEE Conference on Computer Vision and Pattern Recognition*, 2007, pp. 1–8. DOI: 10.1109/CVPR.2007.383248.

[6] A. Lopez Paredes, M. Heredia Conde, and O. Loffeld, "Sparsity-aware 3D ToF sensing," 2022. DOI: 10.36227/techrxiv.19161749.v1. [Online]. Available: https://www.techrxiv.org/articles/preprint/Sparsity-aware%5C_3D%5C_ToF%5C_Sensing/19161749.

[7] M. Heredia Conde, K. Hartmann, and O. Loffeld, "Simple adaptive progressive edge-growth construction of LDPC codes for close(r)-to-optimal sensing in pulsed ToF," in *2016 4th International Workshop on Compressed Sensing Theory and its Applications to Radar, Sonar and Remote Sensing (CoSeRa)*, 2016, pp. 80–84. DOI: 10.1109/CoSeRa.2016.7745704.

[8] M. Heredia Conde, K. Kagawa, T. Kokado, S. Kawahito, and O. Loffeld, "Single-shot real-time multiple-path time-of-flight depth imaging for multi-aperture and macro-pixel sensors," in *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 1469–1473. DOI: 10.1109/ICASSP40776.2020.9054565.

[9] L. Gan, T. T. Do, and T. D. Tran, “Fast compressive imaging using scrambled block hadamard ensemble,” in *2008 16th European Signal Processing Conference*, 2008, pp. 1–5.

[10] X.-Y. Hu, E. Eleftheriou, and D.-M. Arnold, “Progressive edge-growth tanner graphs,” in *GLOBECOM’01. IEEE Global Telecommunications Conference (Cat. No.01CH37270)*, vol. 2, 2001, 995–1001 vol.2. DOI: 10.1109/GLOCOM.2001.965567.

[11] G. Srirutchataboon, A. Bajpai, L. Wuttisittikulkij, and P. Kovintavewat, “Peg-like algorithm for LDPC codes,” in *2014 International Electrical Engineering Congress (iEECON)*, 2014, pp. 1–4. DOI: 10.1109/iEECON.2014.6925956.