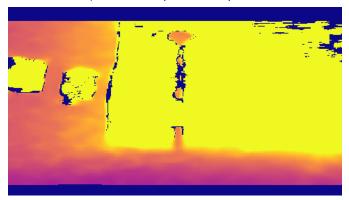
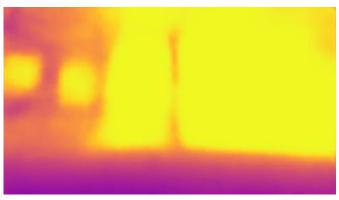


Information-theoretic LiDAR Compression and LiDAR Saliency Maps

Abstract: Information compression methods employ various approaches to achieve their goal and among others may allow the identification of the most salient features in the input data. In this project we want to use information compression over LiDAR data not only to reduce the input size but simultaneously achieve implicit identification and selection of the most (geometrically) salient features in the scene. Accordingly, this can support critical robotic tasks including that of Simultaneous Localization And Mapping (SLAM) especially in areas with weak geometries (e.g., road tunnels). The "palette" of methods considered includes both so-called "traditional techniques" (e.g., exploiting the wavelet transform on depth images, OpenCTM on 3D triangle meshes) either lossless or lossy, as well as neural networks-based techniques such as (variational) autoencoders.





Left: 480x270 depth image, Right: Reconstructed image from compressed latent space involving only 128 variables.

Tasks:

- Study of literature in order to understand the problem of ghost nets.
- Develop vision-based method and system for the detection and classification of ghost nets.
- Develop a (set of) robotic manipulator(s) to a) cut ghost nets, and b) attach balloons for them to be lifted.
- Develop a duo of robotic systems for ghost net detection, cutting and retrieval with the robotic units being tugged by a larger vessel on the surface of the sea.

Literature (indicative):

- [1] Johnson Jr, P.D., Harris, G.A. and Hankerson, D.C., 2003. Introduction to information theory and data compression. CRC press.
- [2] Ahmed, N., Natarajan, T. and Rao, K.R., 1974. Discrete cosine transform. IEEE transactions on Computers, 100(1), pp.90-93.
- [3] Strang, G., 1999. The discrete cosine transform. SIAM review, 41(1), pp.135-147.
- [4] Unser, M. and Blu, T., 2003. Mathematical properties of the JPEG2000 wavelet filters. IEEE transactions on image processing, 12(9), pp.1080-1090.
- [5] Pratt, W.K., Kane, J. and Andrews, H.C., 1969. Hadamard transform image coding. Proceedings of the IEEE, 57(1), pp.58-68.
- [6] Davenport, M.A., Duarte, M.F., Eldar, Y.C. and Kutyniok, G., 2012. Introduction to compressed sensing.
- [7] Donoho, D.L., 2006. Compressed sensing. IEEE Transactions on information theory, 52(4), pp.1289-1306.
- [8] Tsaig, Y. and Donoho, D.L., 2006. Extensions of compressed sensing. Signal processing, 86(3), pp.549-571.
- [9] Duarte, M.F. and Eldar, Y.C., 2011. Structured compressed sensing: From theory to applications. IEEE Transactions on signal processing, 59(9), pp.4053-4085.
- [10] DeVore, R.A., Jawerth, B. and Lucier, B.J., 1992. Image compression through wavelet transform coding. IEEE Transactions on information theory, 38(2), pp.719-746.
- [11] Bora, A., Jalal, A., Price, E. and Dimakis, A.G., 2017, July. Compressed sensing using generative models. In International Conference on Machine Learning (pp. 537-546). PMLR.
- [12] Wu, Y., Rosca, M. and Lillicrap, T., 2019, May. Deep compressed sensing. In International Conference on Machine Learning (pp. 6850-6860). PMLR.

Main supervisor: Kostas Alexis, Professor, NTNU