Learning to See: Perceptual Learning and MRI Image Reconstruction

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Image reconstruction is necessary for many types of imaging, including magnetic resonance imaging (MRI), positron emission tomography (PET), and other tomographic imaging modalities including RADAR and LIDAR. As such images are acquired, they are encoded in an intermediate representation of the imaged object in what is known as the sensor domain. In order for this intermediate representation to lead to an image, the function used to encode the image into the sensor domain, or the encoding scheme, must be inverted in a process called reconstruction. Conventional approaches for image reconstruction are imperfect since analytic forms of the exact inverse transform is not always possible, so methods that require the use of approximations by chains of highly tuned signal-processing modules are used. These "handcrafted" solutions use a chain of handcrafted signal processing modules that require expert manual parameter tuning and often are unable to handle imperfections of the raw data, such as noise.

Inspired by the biological perceptual learning archetype, we have developed a noise-robust image reconstruction approach that is based on a data-driven learning of the low-dimensional manifold representations of real-world data, and is implemented with a deep neural network architecture [1]. AUTOMAP, Automated Transform by Manifold Approximation, is an end-to-end automated k-space-to-image-space generalized reconstruction framework that learns a highly-parameterized image reconstruction function optimized for a corpus of training data, and is less sensitive to input corruptions such as channel noise. In this case, we generated training data by taking a large set of images from natural scenes and reverse-encoding them into the sensor domain via a known encoding function, making paired data sets

The reconstruction performance of AUTOMAP in several regimes will be discussed [1,2], as well as a discussion of the power of these learned approaches as be an essential part to the development and discovery of new pulse sequences.

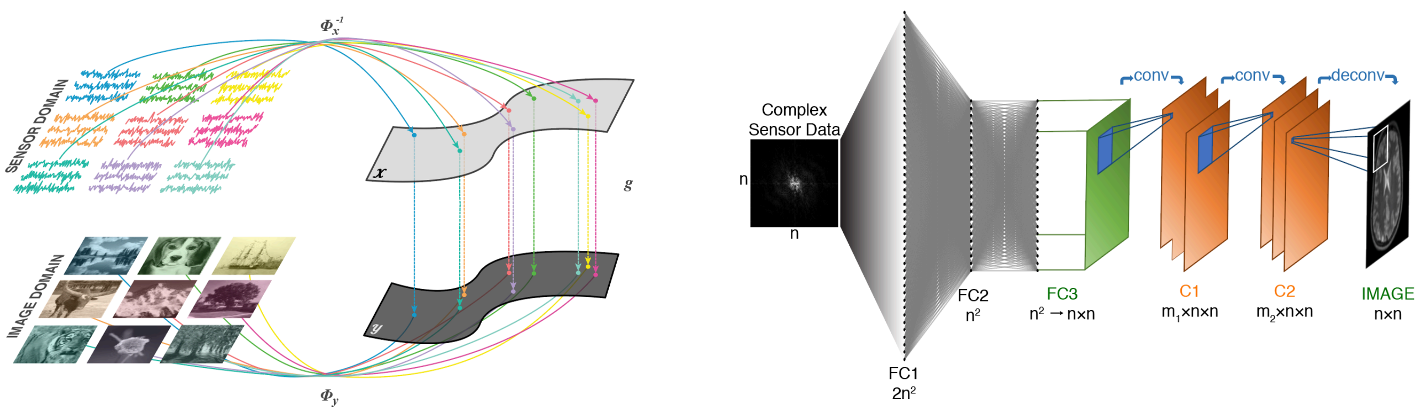

Figure 1**: (Left)** A mapping between sensor domain and image domain is determined via supervised learning of sensor (top) and image (bottom) domain pairs. The training process implicitly learns a low-dimensional joint manifold $\mathcal{X}\times\mathcal{Y}$ over which the reconstruction function $f(x) = \phi_y \circ g \circ \phi_x^{-1}(x)$ is conditioned. **(Right)** AUTOMAP is implemented with a deep neural network architecture composed of fully-connected layers (FC1 to FC3) with hyperbolic tangent activations followed by a convolutional autoencoder (FC3 to Image) with rectifier nonlinearity activations (see Methods for model architecture details). Figure adapted from Reference 1.

REFERENCES:

[1] B. Zhu, J. Z. Liu, S. F. Cauley, B. R. Rosen, and M. S. Rosen, "Image reconstruction by domain-transform manifold learning ," *Nature*, vol. 555, no. 7697, pp. 487–492, Mar. 2018.

[2] N. Koonjoo, B. Zhu, and M. S. Rosen, "AUTOMAP Image Reconstruction — Improved Low Signal-to-Noise MR Data at ultra-low field," presented at the ISMRM workshop on Machine Learning, Asilomar, 2018.