Imaging Acquisition & Reconstruction: Compressed Sensing

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Highlights

- Compressed sensing (CS) is a means to accelerate MR acquisitions by k-space undersampling that exploits a new dimension of data redundancy.
- CS theory tells us that it is possible to recover an accurate image if a) k-space is randomly-undersampled and b) the image is sparse in some transform domain (e.g., finite differences or wavelet).
- CS is particularly attractive for $>$ 2D data acquisitions, where it can be leveraged to achieve greater volume coverage or finer spatiotemporal resolution in dynamic acquisitions, or reduce motion artifacts.
- CS combines synergistically with parallel imaging to achieve higher spatiotemporal accelerations than are possible with either alone.
- CS is a particularly active area of MR research: Every year researchers find new applications, and reconstruction methods that are computationally faster or use better sparsifying transforms.

Target Audience: Students and researchers interested in image reconstruction and scan acceleration techniques.

Outcome & Objectives: The overall goal of this lecture is to introduce students to CS, including:

- Basic CS theory
- The ingredients of a good CS MR acquisition
- How images are reconstructed in a CS framework
- When it might be a good idea to use CS
- What some of the open research problems are

Purpose: Reducing scan time has been a goal of researchers since MRI was first developed. This purpose of this lecture is to introduce students to compressed sensing, one of the most recent general-purpose acceleration techniques to be proposed.

Methods: Compressed sensing is based on the fact that MR images are compressible, meaning that they can be represented by a small number (*much* smaller than the total number of image voxels) of high-amplitude coefficients in some transform domain. That transform domain could be the image domain, for angiograms, or the more generally-applicable wavelet domain for anatomical images, and the image is said to be *sparse* in that domain, because most of its coefficients are zero, and only a few are large. If k-space is then undersampled in a random manner (rather than being uniformly undersampled as in parallel imaging), aliasing artifacts in the image and sparse transform domains are incoherent/look like noise. In the sparse transform domain, that “noise” will be of lower amplitude than the significant image coefficients, so it can be largely removed by thresholding (i.e. the image can be "denoised"), without suppressing significant image signals. This is the basic idea of compressed sensing: data is acquired so that artifacts look like noise, and image denoising is applied to suppress the noise-like aliasing artifacts and recover the image. In practice a CS image reconstruction alternates between denoising the image and forcing it to be consistent with the acquired k-space data. CS is generally applied in combination with parallel imaging, and it provides the most benefit in multidimensional data acquisitions, such as 3D dynamic imaging, where the image is sparse in more than one transformed dimension.

Discussion and Conclusion: Current efforts in compressed sensing MRI research primarily focus on the development of sparse transform that better concentrate MR signals into a few large coefficients, the integration of CS with parallel imaging, the development of computationally faster and more automatic CS reconstruction algorithms, and on clinical applications of CS. This course will be a springboard to help participants get started in developing and applying their own CS acquisitions and reconstructions.

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