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EECE 8396-01
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Proposal: Deep Compressed Sensing fMRI

Motivation:

In medical imaging, we often assume that an image is sampled at the Nyquist rate. That is, we take a sufficient amount of discrete measurements to construct a continuous whole (M > N). In fMRI, we see this phenomenon in slice-timing correction where we interpolate the continuous time series from discrete measurements in order to shift the signals. However, this sampling rate costs time and effort; moreover, if we can only sample below the Nyquist rate, then we could certainly benefit from a method that can recover a signal from fewer measurements. These realities beg the question: if we could sample below the Nyquist rate and solve an underdetermined linear system, can we collect fewer samples and still recover a high-quality image using compressed sensing?

Compressed sensing reconstructs signals by solving underdetermined linear systems under the conditions that the measurements are sparse in the domain and incoherent and that some known prior structure exists in the data, i.e., measurements along some basis. In fMRI, compressed sensing is challenging because the temporal dynamics of hemodynamic signals are relatively slow compared to other fast-acquisition signals that historically benefit from compressed sensing. Additionally, fewer samples insinuates a loss of statistical power in subsequent analyses. However, discerning a signal and quickly turning over an analysis has practical benefit.

Related problems: data imputation and denoising through deep inverse solving.

Goal:

- Explore compressed sensing for reconstructing under-sampled fMRI time series.
- Devise a method / develop a deep learning-based model to solve compressed inverse problems.
- Recover a signal with compressed sensing and analyze the data.

Data:

Find a dataset that samples below the Nyquist rate
OR
Simulate undersampling on a public dataset

Method:

Building upon:

- Li, X., Cao, T., Tong, Y., Ma, X., Niu, Z., & Guo, H. (2020). Deep residual network for highly accelerated fMRI reconstruction using variable density spiral trajectory. *Neurocomputing*, *398*, 338-346.
- Zong, X., Lee, J., Poplawsky, A. J., Kim, S. G., & Ye, J. C. (2014). Compressed sensing fMRI using gradient-recalled echo and EPI sequences. *NeuroImage*, *92*, 312-321.
- Yang, Z., Zhuang, X., Sreenivasan, K., Mishra, V., Curran, T., & Cordes, D. (2020). A robust deep neural network for denoising task-based fMRI data: An application to working memory and episodic memory. *Medical image analysis*, *60*, 101622.
- Sato, M. A., Yoshioka, T., Kajihara, S., Toyama, K., Goda, N., Doya, K., & Kawato, M. (2004). Hierarchical Bayesian estimation for MEG inverse problem. *NeuroImage*, *23*(3), 806-826.

Timeline:

Before spring break: problem formulation, dataset defined,
Two weeks after break: rudimentary implementation
Milestone: some results
Two weeks after milestone: most results
Presentations: all results