# Deep Learning Dynamic MRI Reconstruction

Assignments

April, 2025

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**Deadline: Presentation, April 23rd; Report, April 27th**

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Your report should include answers to all the questions. Please comment and clearly justify your answers. The Python code and report need to be **uploaded to the Blackboard** system before the deadline. You need to submit: 1) All the **Python files** that you have generated and 2) A **report**, in pdf with the obtained figures, answers and detailed comments. Failure to submit code will result in a **40% reduction** of the assignment mark. **Only one group member is needed to submit the report. Remember to list the names (in Chinese) of all group members in the report**.

Detailed tasks for the first project can be found in the 'Deep Dynamic MRI recon project-2025.pdf' file.
Basically, there is a total of **30 marks** for this project report. However, **5 additional marks** can be gained if you could do the extra task (the last one).
The deadline for this project is **April 23rd. You are supposed to give a presentation of this project on that day, which will count for another 15 marks. However, you have several more days to write the report, which should be submitted before April 27th.**

# Provided Material

- **cine. npz** Fully sampled cardiac cine MR images with size of [nsamples, nt, nx, ny], where nsamples = 200 is the total number of data samples; nt is the number of dynamic frames; nx, ny indicates the size of each 2D dynamic image, respectively.

- **CS_mask.py** This function generates 2D variable-density undersampling masks for a dynamic sequence.

- **example.ipynb** This file gives some example codes for loading the dataset, showing example cine data and calling the CS_mask function.

# Assignment

(a) ***(5 marks)*** Generate a variable density random undersampling pattern ($U$) with the size of the given cine images for acceleration factor of **5. Eleven** central k-space lines are sampled for each frame. Each sampling pattern must be a matrix with 1s in the sampled positions and 0s in the remaining ones. Plot the undersampling mask for one dynamic frame and undersampling masks in the ky-t dimension. Is the sampling mask the same for different dynamic frames? Obtain the aliased images as a result of undersampling with the generated patterns. For this you should use:

$$b = F^{-1}UFm$$

where $m$ is the fully sampled image, $U$ is the corresponding undersampling pattern, $F$ is the Fourier transform and $b$ is the aliased image. Depict the aliased images and compare them against the fully sampled image.

(b) ***(15 marks)*** Split the cine dataset into training, validation and testing with a ratio of 4:1:2. Construct a standalone denoising network to denoise the undersampled images. To explore **the temporal correlation**, consider stacking the dynamic images along the channel dimension or using 3D CNN or (2D+1D) CNN. Design your own CNN network for the denoising task. You can use UNet, ResNet or DenseNet, or other fancy neural networks. Plot your training loss and validation loss. Note that if your network is too complex, if may not be able to fit in the current GPU. Show example testing images before and after deep learning reconstruction. And comment on the denoising/dealiasing performance. Calculate the **PSNR** and **SSIM** for each testing slice before and after deep learning reconstruction.

Report the mean and standard deviation of the PSNR and SSIM considering all the testing slices. You may use the PSNR and SSIM calculation functions provided in the demo class.

(c) (**7 marks**) You should have already used weight regularization in your training in (b). Try to add **drop out** and **dynamic learning rate** to you network training. By calculating the testing PSNR and SSIM, please report whether you have observed any improvements by adding them.

(d) ***(3 marks)*** You should have used L2 loss (mean squared error) to train the network. Try to use L1 loss (mean absolute error) to train the network in (c). Which loss yields higher PSNR and SSIM in the testing dataset?

(e) ***(5 additional marks)*** Construct an unrolled deep learning reconstruction network by cascading the denoising network you used in (b) with the data consistency layer. Increase the number of unrolled iterations (the number of unrolled iterations may be limited by the GPU memory and you may need to reduce your batch size for this task), and observe how the reconstruction performance changes by visually comparing the reconstructed images and calculating the PSNR and SSIM.