**Design**

Firstly, we load the data by using *data\_loader.ipynb*, and then we show slices in the sample as k-space data and transform k-space data to real images and ground truth. K-space is an abstract space (three-dimensional space) or a plane (two-dimensional space). As MR imaging data is arranged at a specific K-space position according to different spatial frequencies, and finally transformed into an image, so all we need to do is to transform k-space data to real images and compare the original image and the output image by SSIM. Explicitly, K-space uses spatial frequency as the unit (Hz / cm), the spatial frequency K is described by the three mutually perpendicular components Kx, Ky, and Kz. These three vectors correspond to a three-dimensional frequency space, so this abstract space is called K-space.

Then, we will train the neural network model by U-net based on CNN. When it comes to classification, the information provided by the pixels is always taken into account. However, this information generally includes two types: one is environmental field information, and the other is detailed information. The pixel-based approach has a great deal of uncertainty about the choice of the form. Choosing a size that is too large not only requires more pooling layers to make the environmental information appear, but also loses the local detailed information. But U-net uses a network structure that includes down sampling and up sampling. Down sampling is used to gradually display the environmental information, and the process of up sampling is to combine the down sampling information of each layer and up sampling input information to restore the detailed information, and gradually restore the image accurately. Besides, U-Net combines the location information from the down sampling path to finally obtain a general information combining localization and context, which is necessary to predict a good segmentation map.

For model trained by CNN-convolutional neural network-it is mainly used for image recognition and classification. It consists of input layer, convolution layer, pooling layer, fully connected layer (*Affline* layer), and *Softmax* layer. There is also a very important structure in convolutional neural networks: filters, which act between layers (convolution layers and pooling layers) and determine how to convolve and pool data.

For Loss Function, we will add a function calculating MSE (Mean Square Error) to give our model feedbacks to improve the performance in reconstruction.



After gaining the output images, we can transform them to ground truth to make a comparison. And the value range of SSIM is [0,1], which means the larger the value is, the better the performance is. Structural similarity (SSIM) is also a full-reference image quality evaluation index. It measures the similarity of two images from the aspects of brightness, contrast, and structure. The SSIM algorithm is designed to take into account the visual characteristics of the human eye and it is more in line with the human eye's visual perception than traditional methods. MSE or PSNR algorithms are both evaluations of absolute errors. For the fuzzy changes in the human's perception of the structural information of the image, the model also introduces some perception phenomena related to the changes in perception, including the brightness mask and the contrast mask. The structural information refers to the internal dependency between pixels, especially amongst pixels that are close in space. These dependencies carry important information on the target's visual perception.

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