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C^3-Net: Complex-valued Cascading Cross-domain CNN for accelerating CMR imaging

MICCAI-SCMR Joint Workshop

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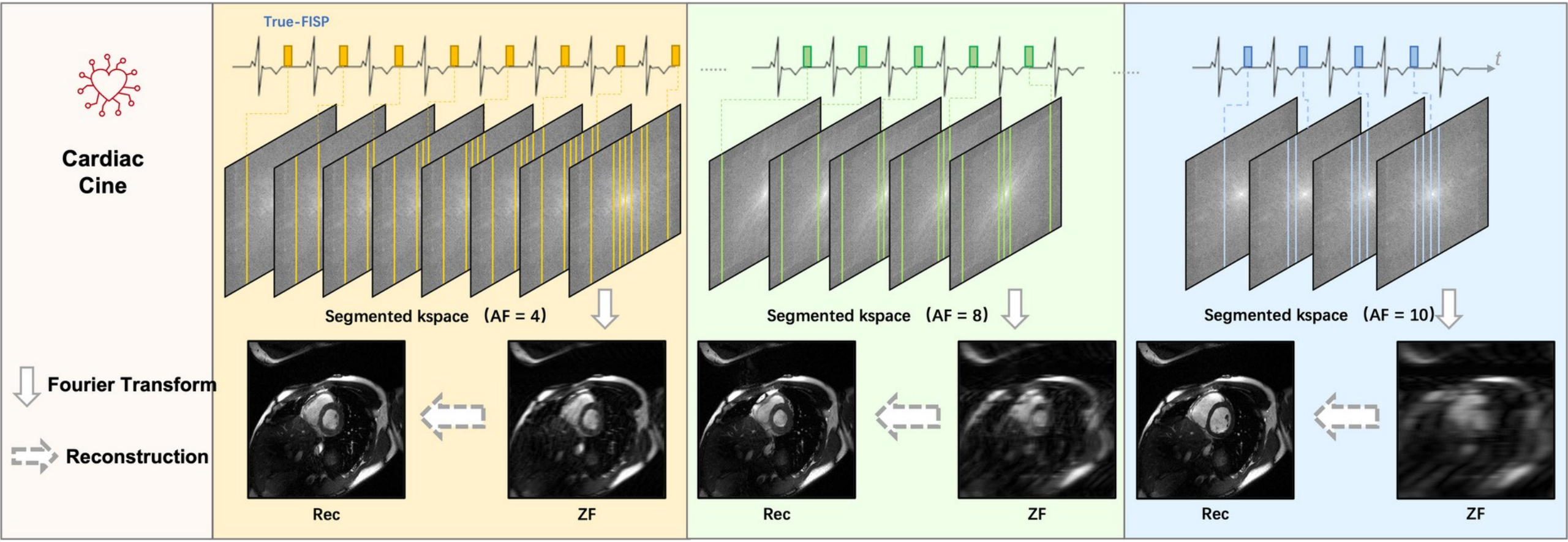
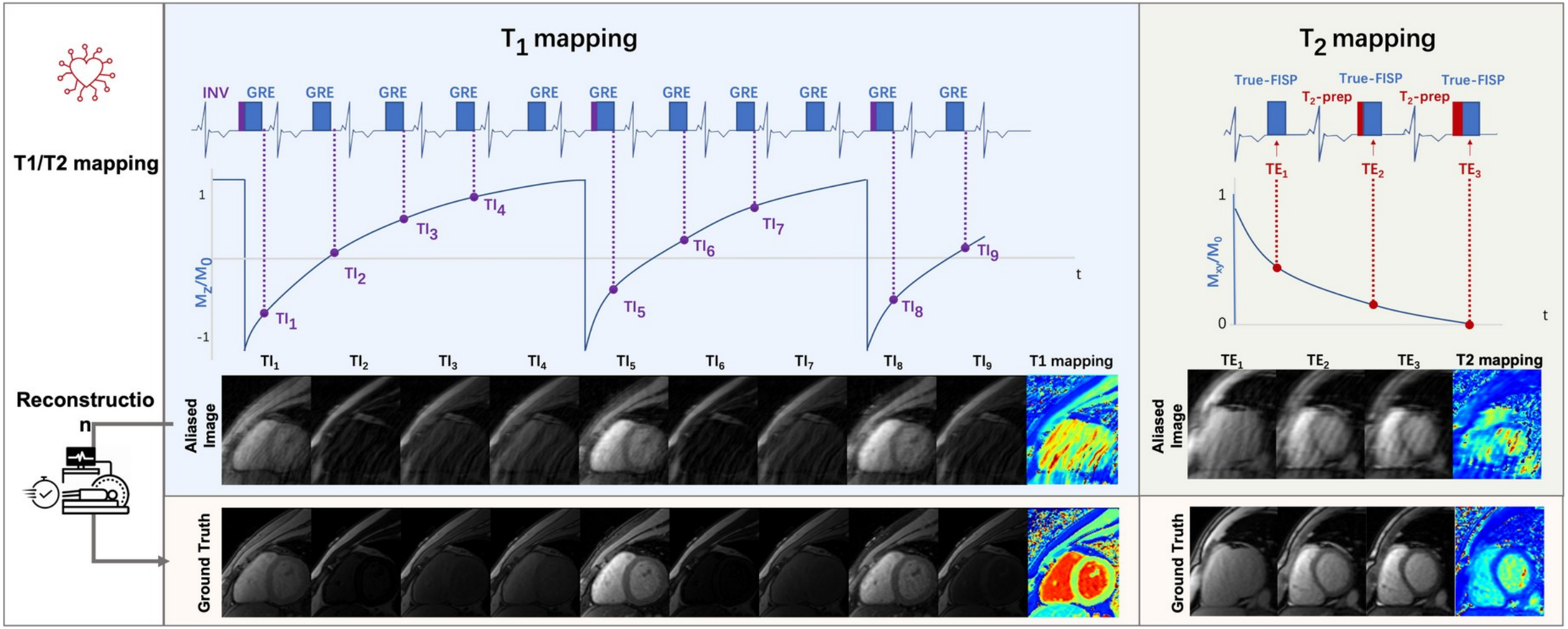
31 Jan 2025

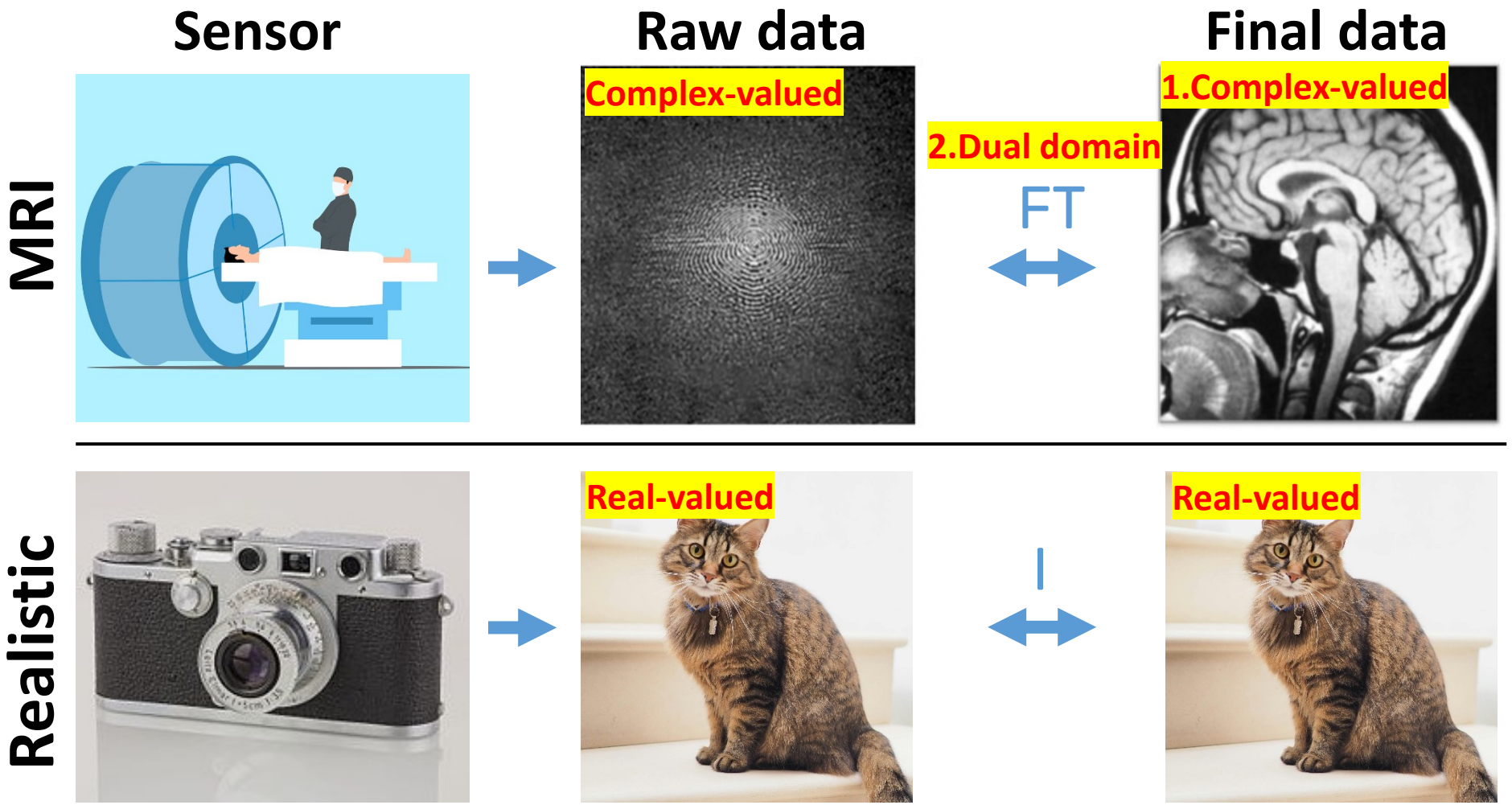
[CMRxRecon 2023] Task 1: Accelerated cine reconstruction ($R = 4, 8, 10$)



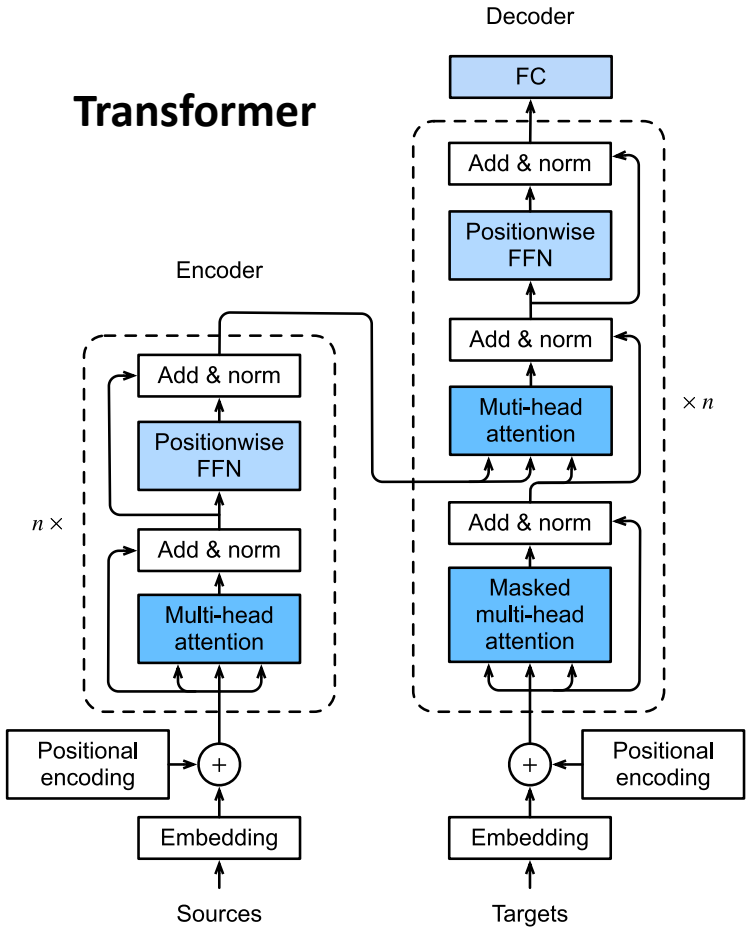
[CMRxRecon 2023] Task 2: Accelerated T1/T2 mapping



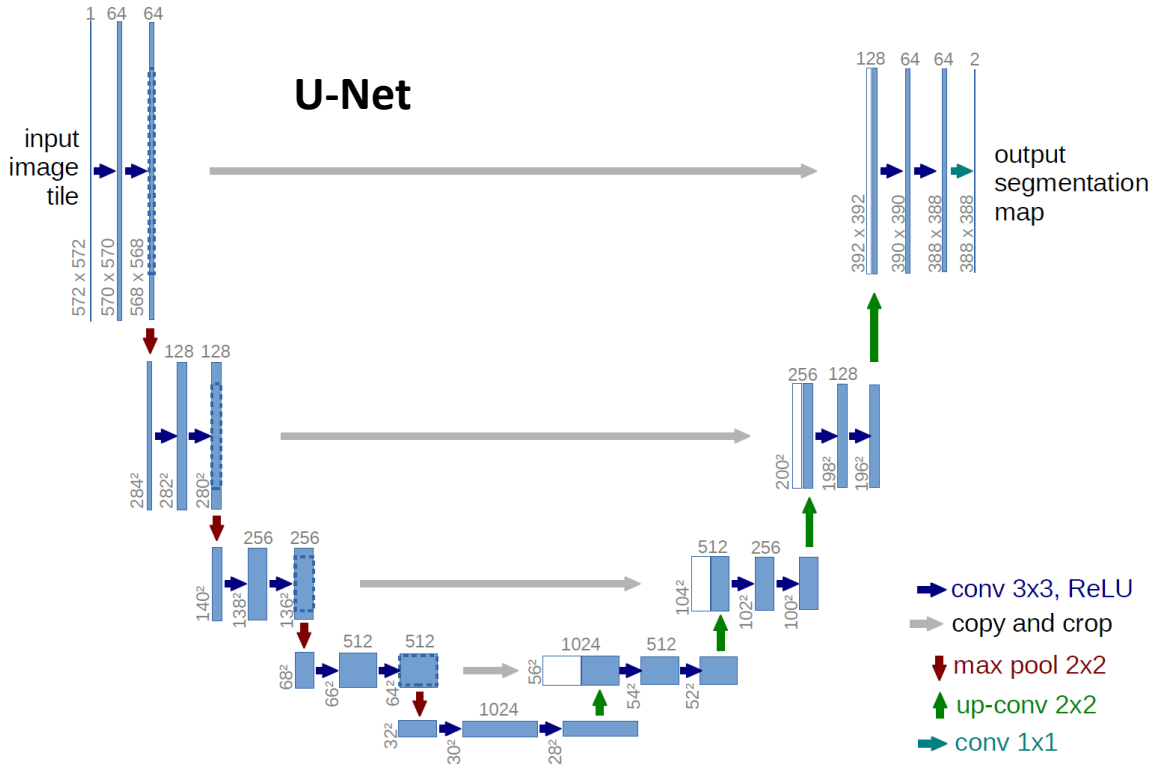
MR images are complex-valued images which are the inverse (non-uniform) Fourier transforms of the raw data (or k-space data).



Decision on Backbone: Transformer or Unet



OR



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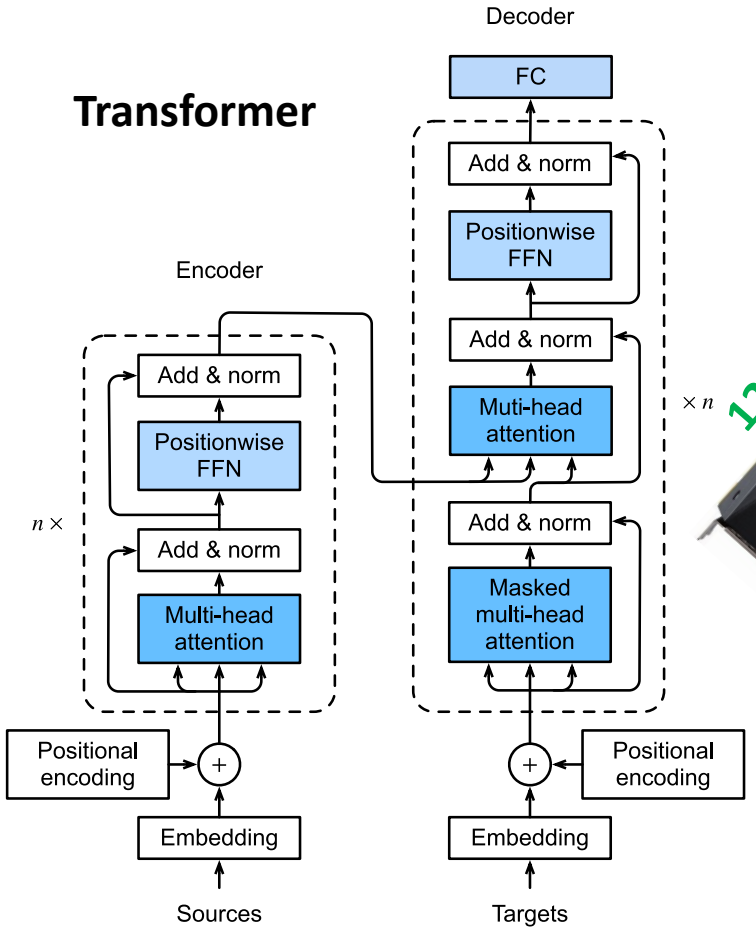

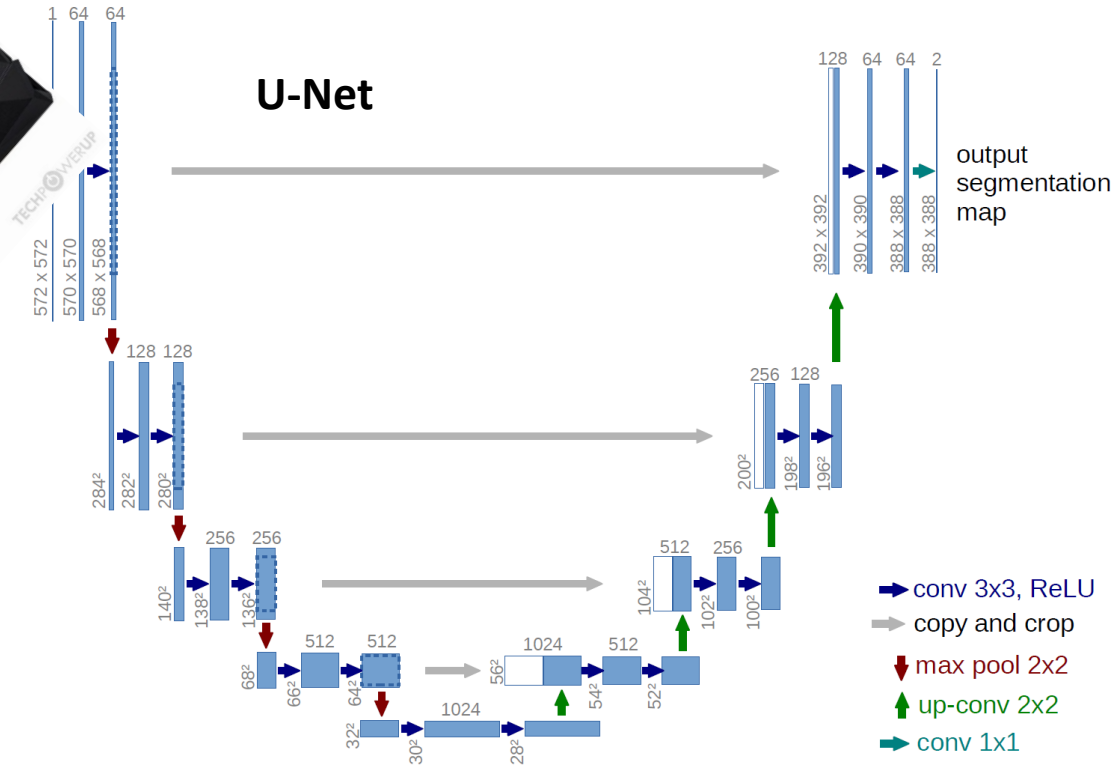

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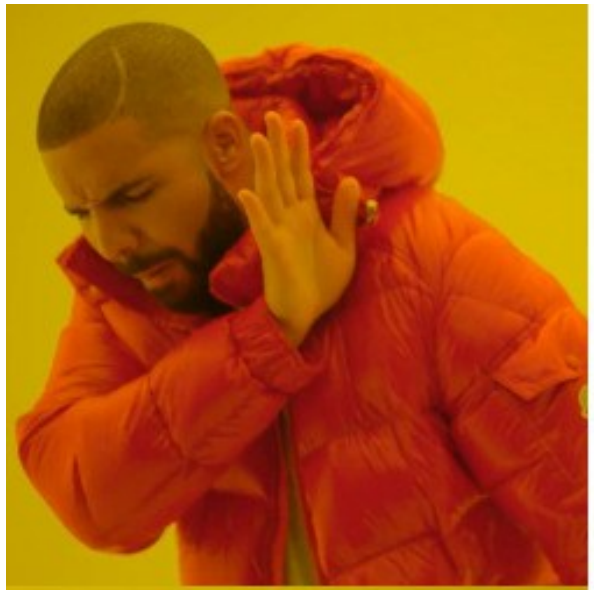
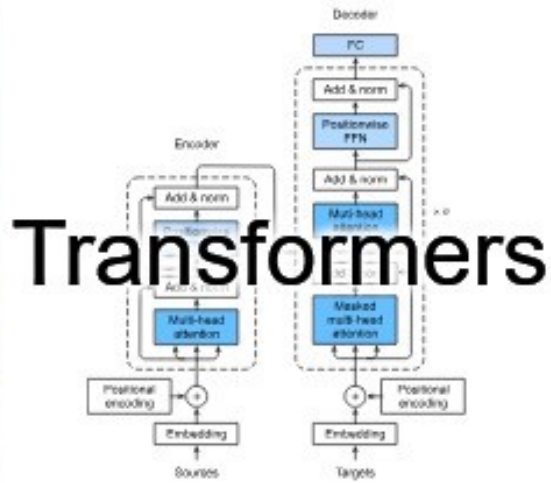
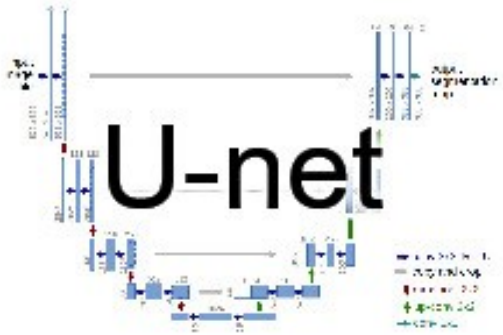
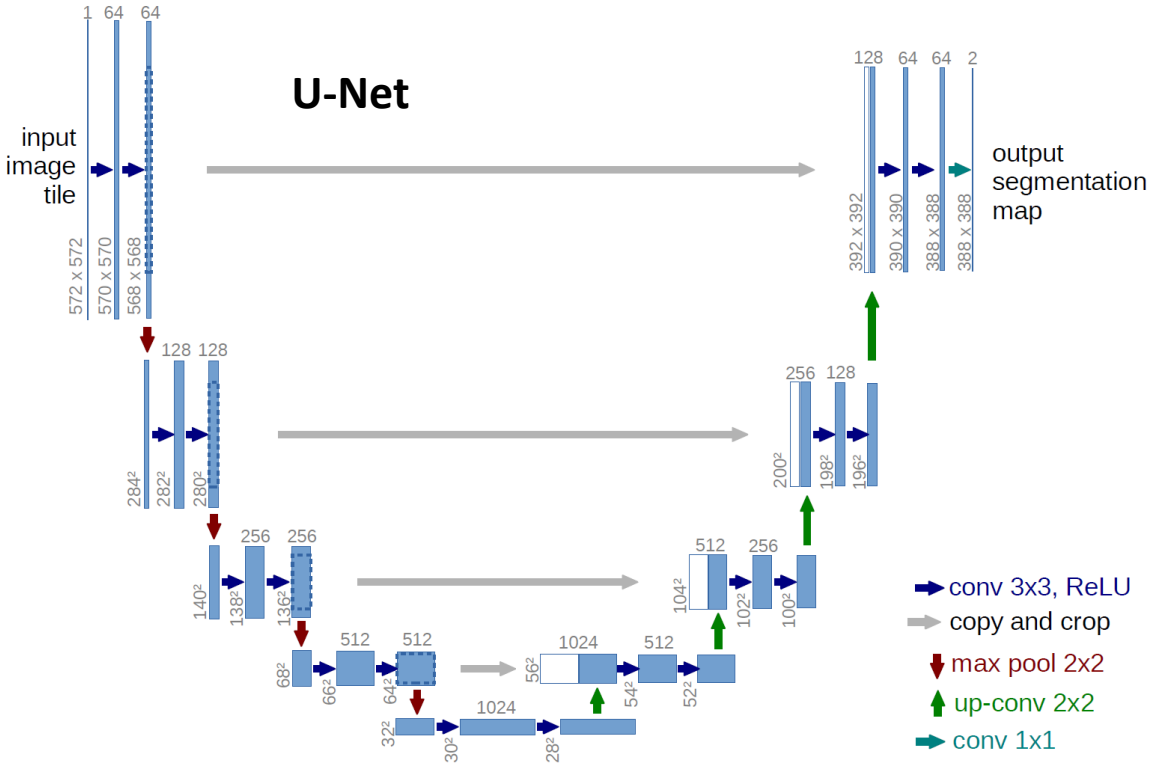
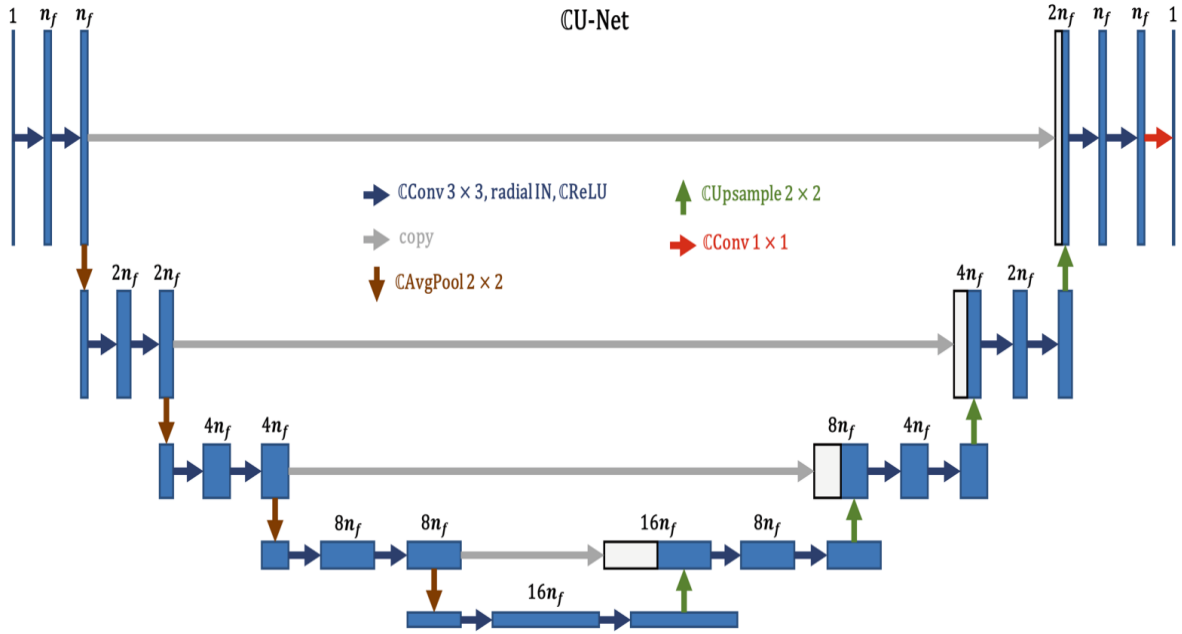






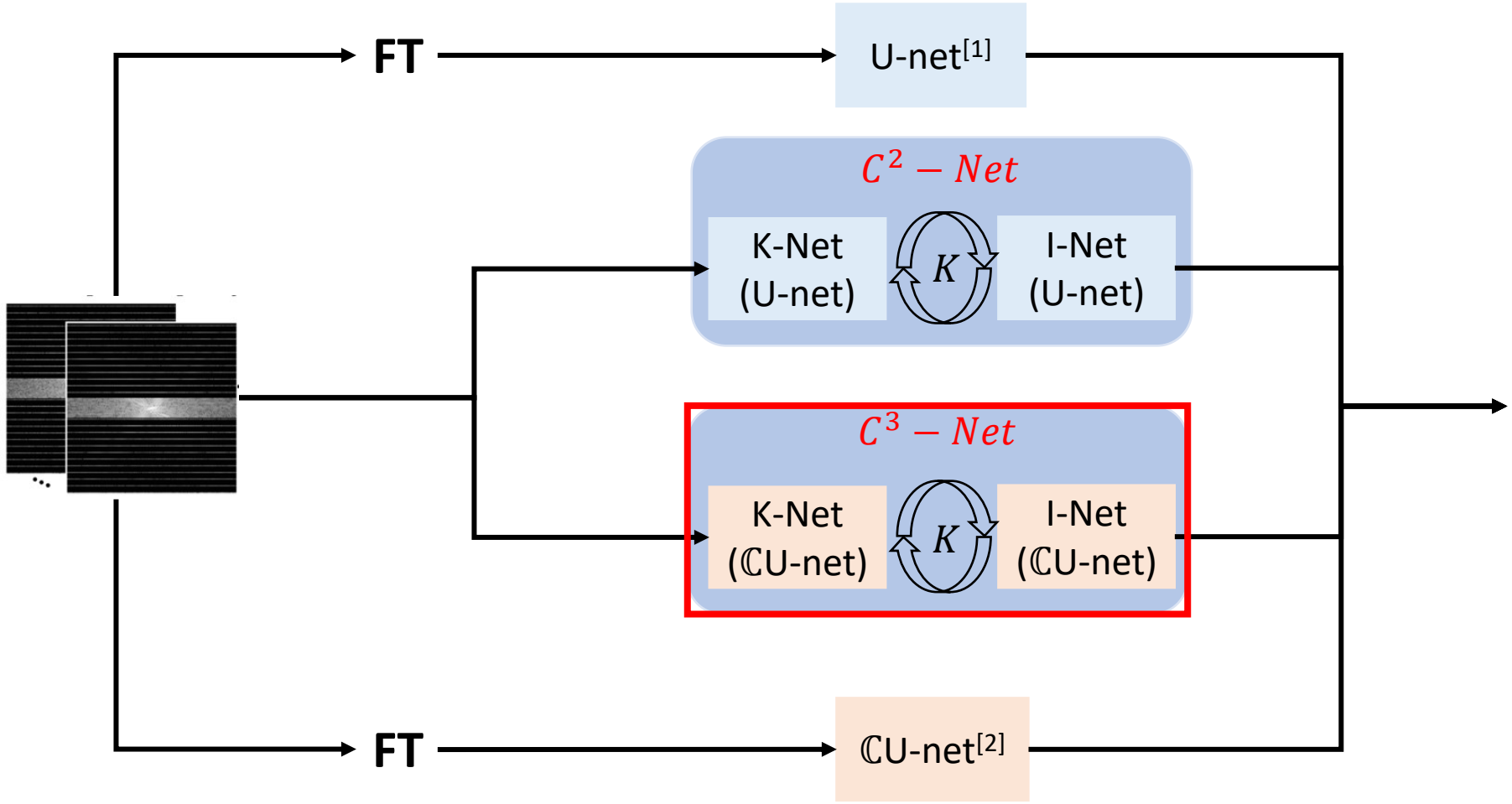
Build ℂU-net according to complex-valued features





[1] Ronneberger O et al. arXiv (2015)
[2] Cole E et al. MRM(2021)

Choose network structure according to dual-domain features



[1] Ronneberger O et al. arXiv (2015)
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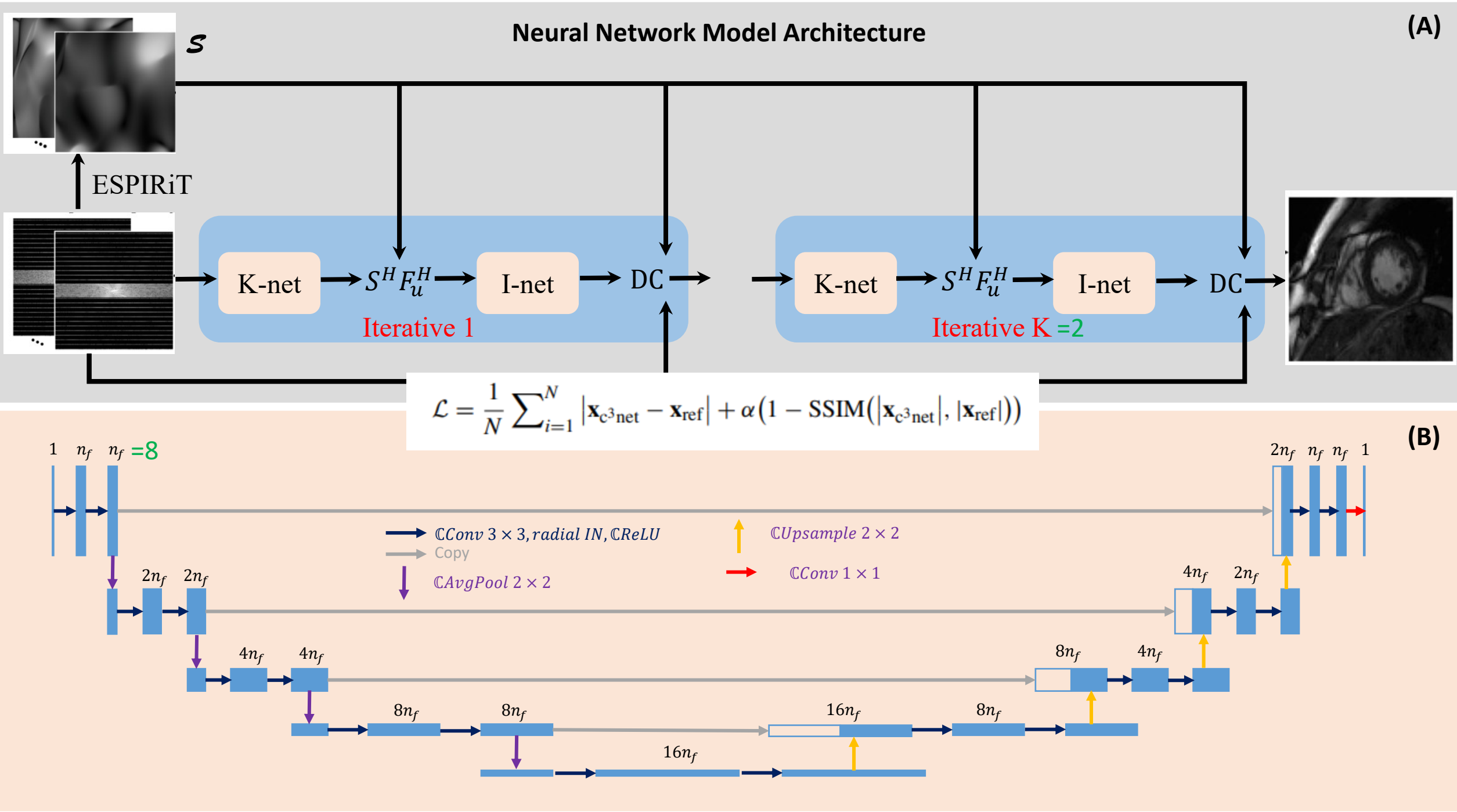
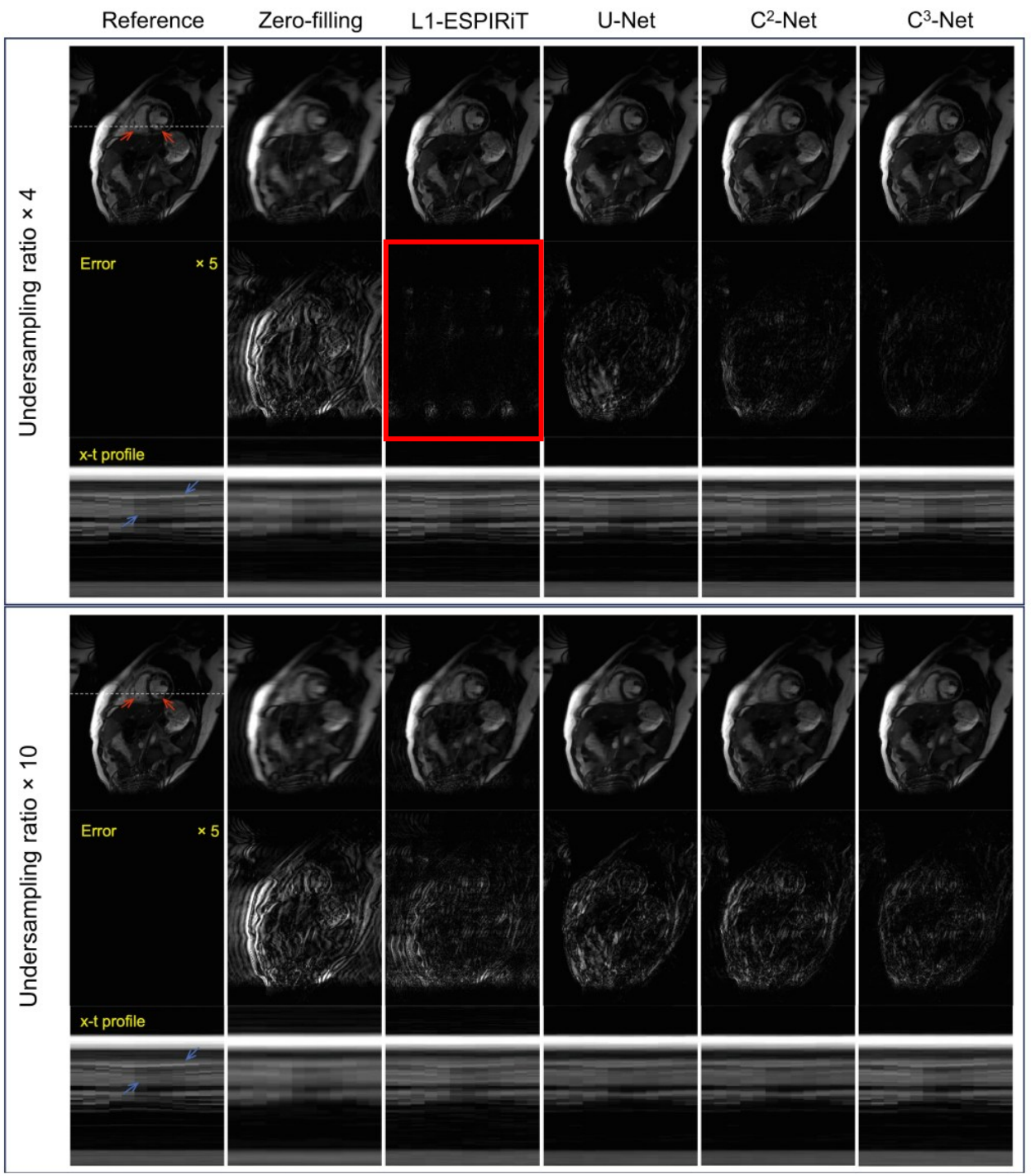
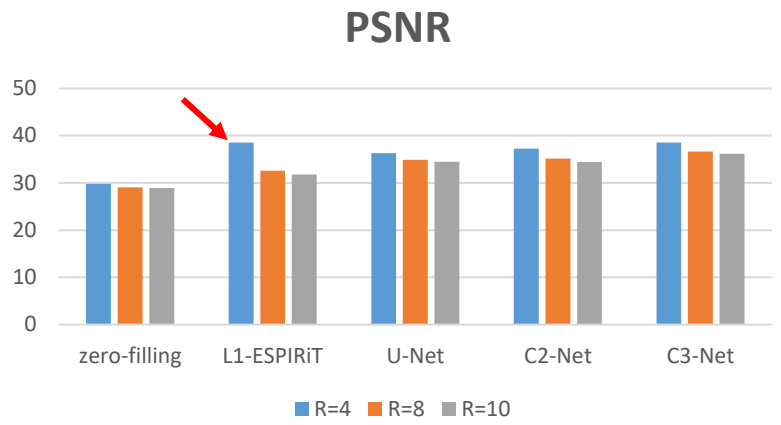
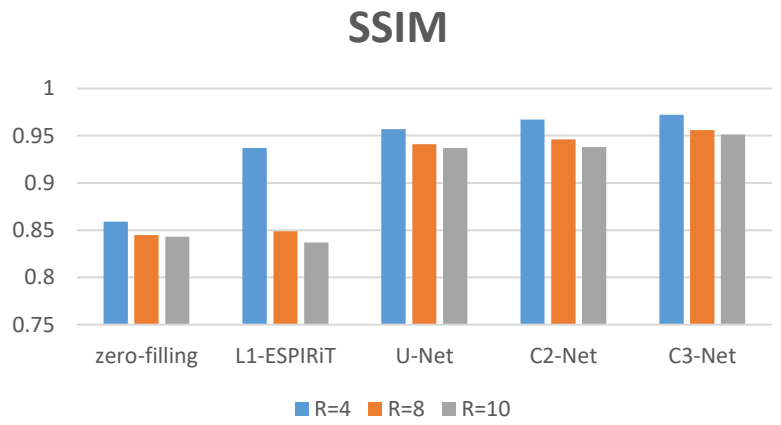
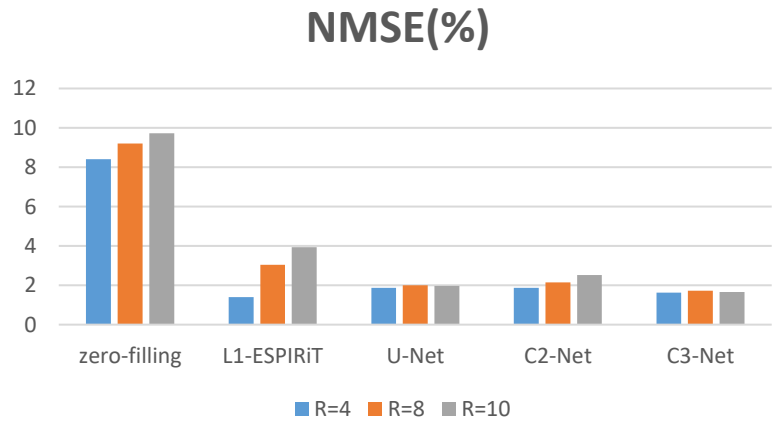

Neural Network Model Architecture
(A)
S
ESPIRiT
K-net
$S^H F_u^H$
I-net
DC
Iterative 1
K-net
$S^H F_u^H$
I-net
DC
Iterative K =2
$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} |\mathbf{x}_{c^3\text{net}} - \mathbf{x}_{\text{ref}}| + \alpha\left(1 - \text{SSIM}\left(|\mathbf{x}_{c^3\text{net}}|, |\mathbf{x}_{\text{ref}}|\right)\right)$
(B)
1 n_f n_f =8
$\mathbb{C}Conv\ 3\times3, radial\ IN, \mathbb{C}ReLU$
Copy
$\mathbb{C}AvgPool\ 2\times2$
$\mathbb{C}Upsample\ 2\times2$
$\mathbb{C}Conv\ 1\times1$
$2n_f$ $2n_f$
$4n_f$ $4n_f$
$8n_f$ $8n_f$
$16n_f$
$16n_f$
$8n_f$ $4n_f$
$4n_f$ $2n_f$
$2n_f$ n_f n_f 1


Reference
Zero-filling
L1-ESPIRiT
U-Net
C2-Net
C3-Net
Undersampling ratio × 4
Error
× 5
x-t profile
Undersampling ratio × 10
Error
× 5
x-t profile


PSNR
50
40
30
20
10
0
zero-filling
L1-ESPIRiT
U-Net
C2-Net
C3-Net
R=4
R=8
R=10


SSIM
1
0.95
0.9
0.85
0.8
0.75
zero-filling
L1-ESPIRiT
U-Net
C2-Net
C3-Net
R=4
R=8
R=10


NMSE(%)
12
10
8
6
4
2
0
zero-filling
L1-ESPIRiT
U-Net
C2-Net
C3-Net
R=4
R=8
R=10

Conclusion & Discussion

- C^3-net proved to be an excellent neural network for dynamic CMR imaging compared to C^2-net, U-net, and conventional CS-based methods.
- The current C^3-net can be further improved by utilizing advanced GPU to increase the number of iterations (K) and the number of filters (n_f)…
- Incorporating spatial-temporal correlation may further improve the quality of reconstructed images.
- It's worthwhile to apply C^3-net to phase-based MR cases, such as fat-water separation, EPI ghost artifact correction, and MR thermometry…

Questions?