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Ai-force

SNU fastMRI challenge

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Methods : E2Evarnet & MRAugment

- Our best score(**SSIM : 0.9858**) was recorded when E2Evarnet[1] and data augmentation[2] were used together.

Our main researches are :

1. Extensively explored the various settings of E2Evarnet, to maximize varnet performance at a given memory requirement.

2. Systematically analyzed the hyperparameters of MRAugment, found that the best results were recorded in the schedule strategy divided into two stages.

3. Various attempts have been made to solve the smoothing problem. In particular, we tried training CGAN at various checkpoints, and found that Discriminator always failed to train. It seems that an expressive model is needed rather than the commonly used discriminator.

E2Evarnet

- Tried several methods such as
  - XPD net
  - Deep J Sense
  - Swin transformer

  But showed much lower performance compared to E2E varnet
- Hyperparameter search by changing depth and width while maintaining model capacity.

cascade : 3
channel : 18
ssim : 0.9821

cascade : 6
channel : 13
ssim : 0.9843

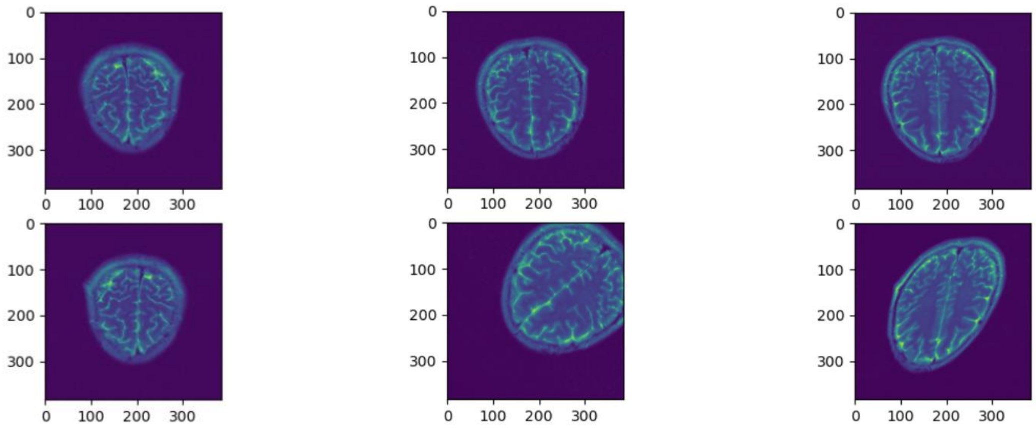
cascade : 12
channel : 5
ssim : 0.9835

MRAugment

- MRAugment(Zalan Fabian et al., 2021) is data augmentation that preserve noise statistics of parallel MRI images.
- We need to determine the parameter values such as: aug_schedule, aug_delay, aug_strength, max rotation, max shearing …

Original

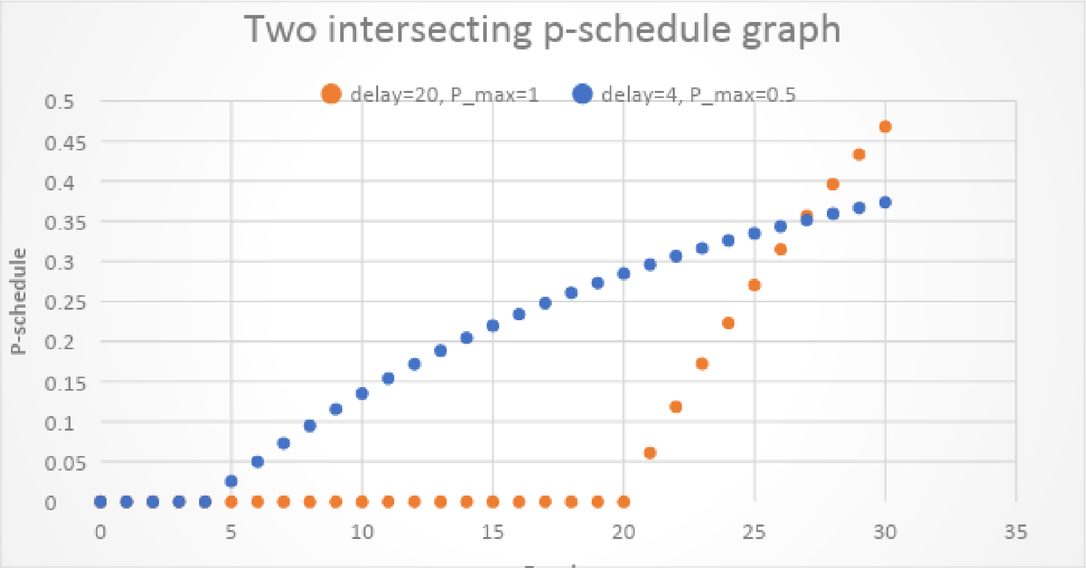
Augmented



Schedule_p 0.096 0.198 0.396

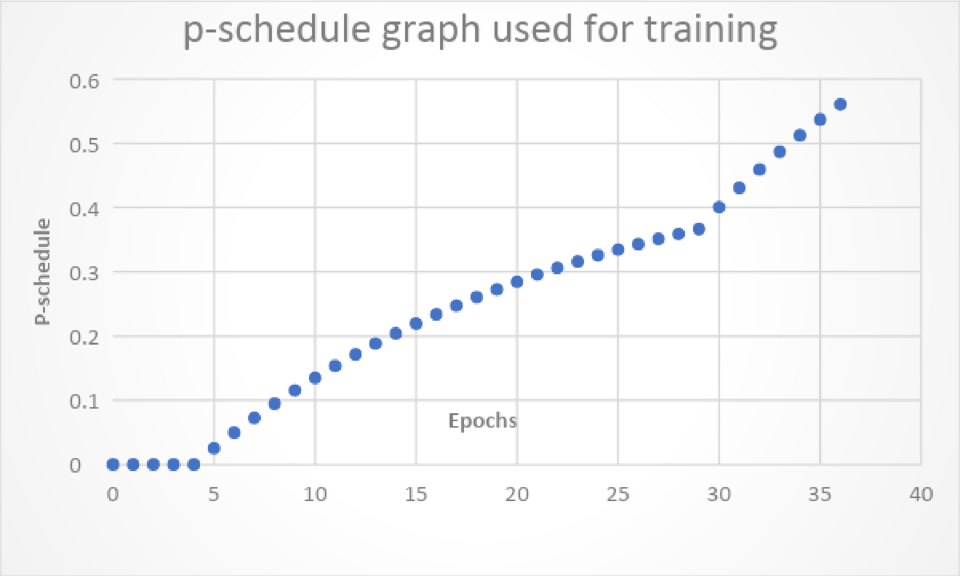
MRAugment – schedule calculator

- Schedule_p value determines the degree of augmentation.
- We developed schedule calculator to systematically analyze effect of p-schedule.



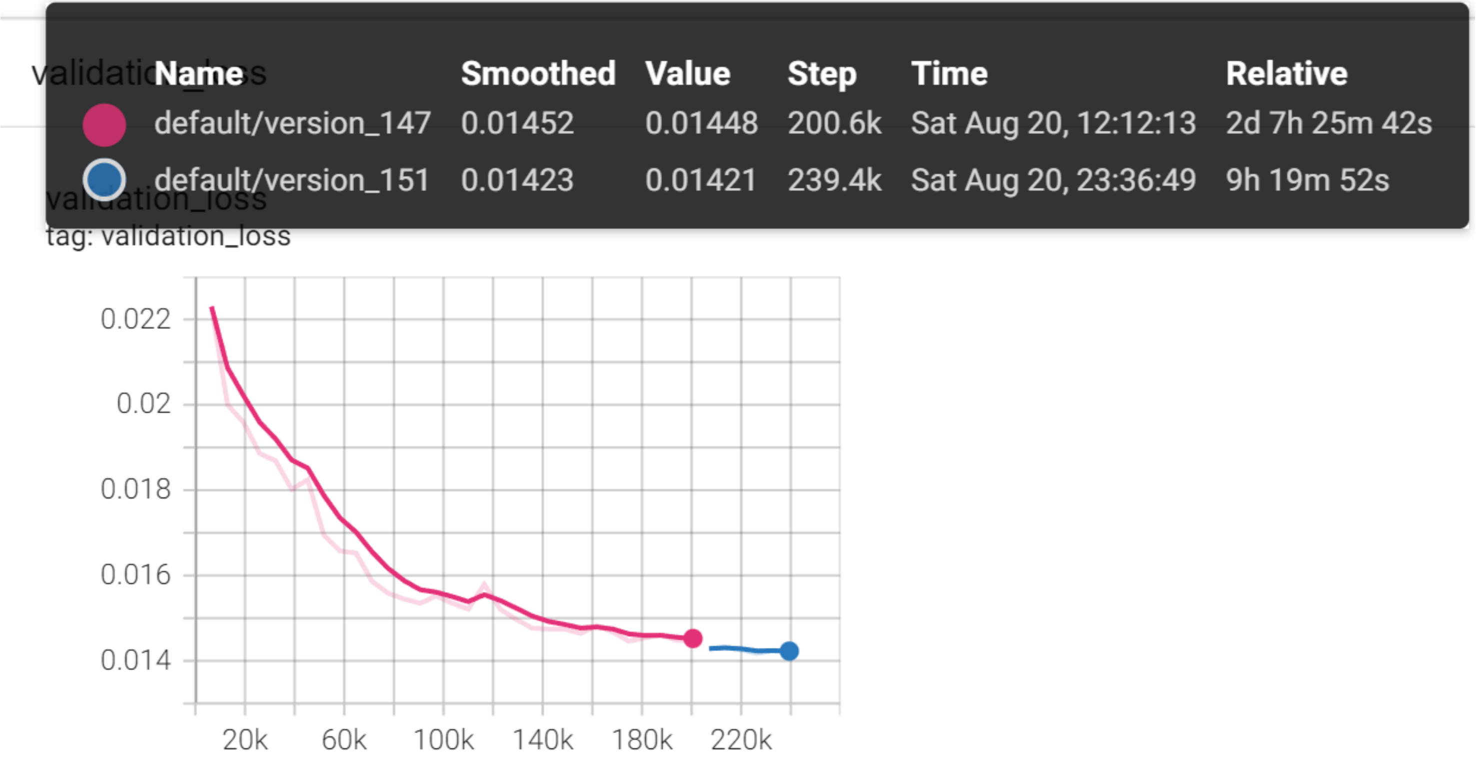
MRAugment – schedule strategy

- The best results were obtained when the two exp graphs were combined and the degree of augmentation increased rapidly at 30 epochs.



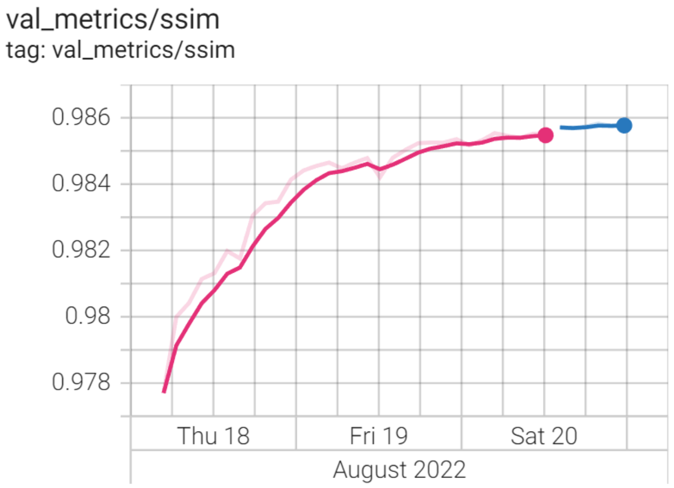
MRAugment – schedule strategy

- Result of our schedule strategy.



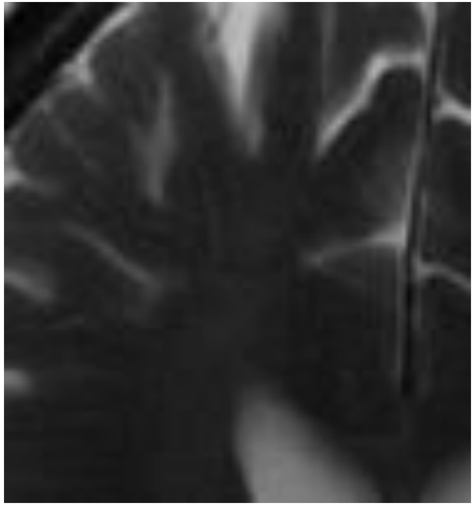
Drawbacks

- Data augmentation started too late. Competition ended before reaching the convergence value.

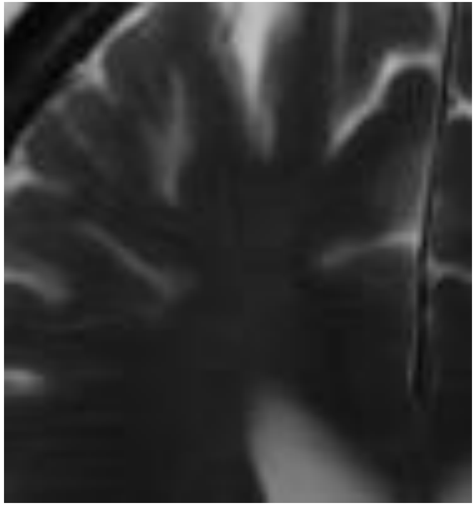


- For personal regret and curiosity, we continued to train few epochs. We will not comment on this results as this may undermine the fairness of the competition.

Smoothing problem (failed attempts)



Target

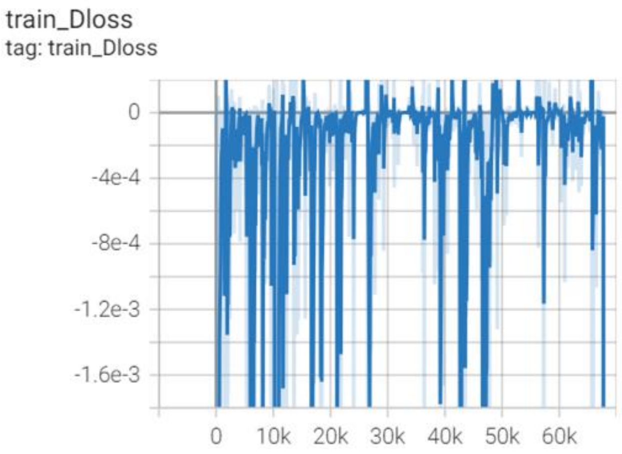


Reconstructed

Model obscured small structures, smoothing the reconstructed image.

CGAN (Vanilla CGAN, WGAN)

- CGAN was used. Discriminator receives (grappa image, reconstructed image) pair as input and train to discriminate it from (grappa image, target image).
- When using a vanilla CGAN with a sigmoid layer in the discriminator, saturation always occurred. In the case of **WGAN without sigmoid layer, saturation did not occur, but discriminator loss was very unstable.**



WGAN - Result

- Starting point of WGAN learning
  1. Initial checkpoint (0 epoch ~ 5 epoch): Learning is possible with adversarial loss. **However, it slows down the convergence speed as learning progresses.**
  2. Late checkpoint (10 epoch ~) : Discriminator is not trained at all.

- Mode collapse occurs (discriminator fails to learn).

  A simple discriminator structure cannot distinguish a reconstructed image from a target image. Creating a more expressive model might solve this. But we couldn't try it because of the memory requirement of the server.

Other methods

- Two approaches to solve image smoothing
  1. Offer more information to model
     L1 loss in k-space domain
     Train with entire image instead of center cropped image
     Use pruno[3] to fill in masked part of kspace, before training
     ➔ There was some improvement, but it was not applied with data augmentation.

  2. Use half precision to enlarge model size
     ➔ Failed to converge

- Memory size of gpu was bottleneck of this competition.
  Since kspace data consumed a lot of memories, we tried models from image domain.
  This showed good performance compared to other models in kspace domain.
  However, we failed to complete training due to lack of time.

Conclusions

- We recorded 0.9858 SSIM score mainly using E2Evarnet and data augmentation.
- Extensively explored the various settings of E2Evarnet, find the optimal depth and width conditions for a given memory requirement.
- For MRAugment, the best results were obtained when the two exp graphs were combined and the degree of augmentation increased rapidly at 30 epochs.
- In the GAN-based approach, we found that WGAN without a sigmoid layer should be used. And discriminator should be expressive enough to distinguish between reconstructed images and target. However, we haven't experimented with sufficiently expressive models because of memory requirements.

References

[1] Sriram, Anuroop, et al. "End-to-end variational networks for accelerated MRI reconstruction." International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2020. (https://github.com/facebookresearch/fastMRI)

[2] Fabian, Zalan, Reinhard Heckel, and Mahdi Soltanolkotabi. "Data augmentation for deep learning based accelerated MRI reconstruction with limited data." International Conference on Machine Learning. PMLR, 2021. (https://github.com/MathFLDS/MRAugment)

[3] Zhang J, Liu C, Moseley ME. “Parallel reconstruction using null operations.” Magn Reson Med. 2011 Nov;66(5):1241-53.

Our codes (https://github.com/jun-pac/SNU-fastMRI-22-summer)