Applying supervised deep-learning for improving quantitative susceptibility map (QSM) from noised local field map

Eunju Sung, supervisor: Jong-ho Lee (B)

Abstraction

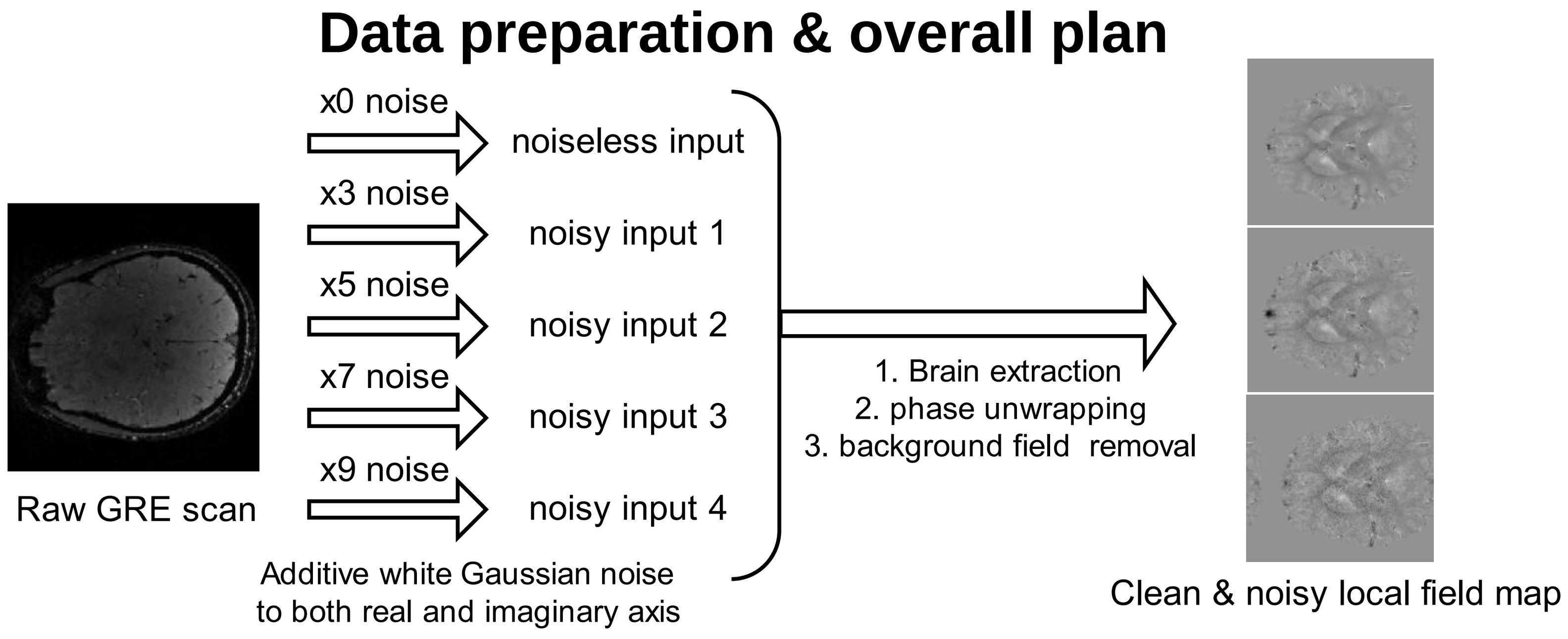
The complexity of noise in MR images necessitate sophisticated denoising solutions and deep-learning models are emerging as effective denoising tools. Unet, an adaptive supervised deep-learning model which are commonly used in biomedical imaging field, stands out as a viable option for MR image denoising. Among various MR images, quantitative susceptibility mapping (QSM) holds promise for enhanced medical diagnosis by revealing diverse anatomical and pathological structures not visible in conventional T1 or T2 MR images. Here, I suggest a cascade model comprising a 3D/2D Unet denoiser and QSMnet, capable of robust QSM mapping even in the presence of noisy local field maps. The cascade model yields better QSM maps if the input local field maps were noised. However, when applied to clean local field maps, the performance was better when using QSMnet alone. This study shows the effectiveness of 3D/2D Unet for MR images and the necessity of introducing denoising methods when dealing with potentially highly noised images.

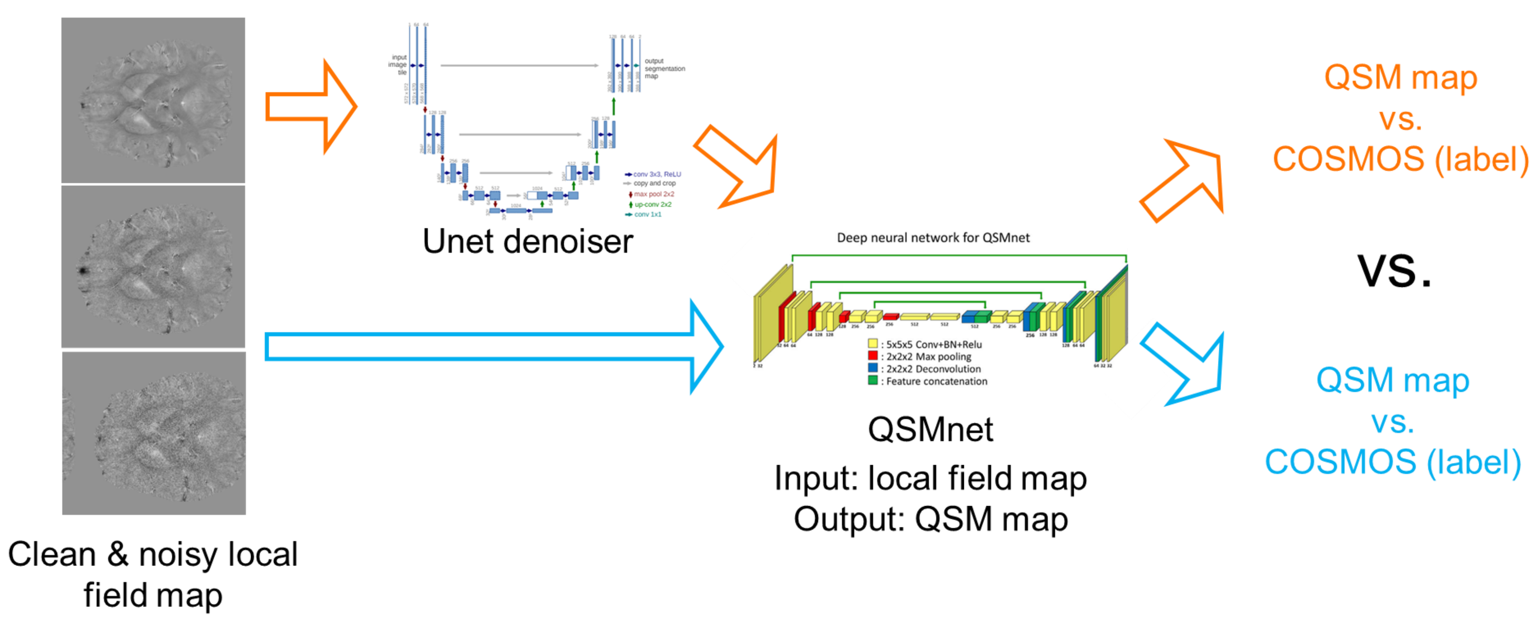
Introduction

- **Quantitative susceptibility map (QSM)** has potential for better medical diagnosis because it can reveal various anatomical & pathological structures
- **QSMnet**, which is based on supervised deep-learning model **3D-Unet**, showed comparably good QSM mapping
- **Noise property of MR images is highly complex**; deep-learning based model can be good solution for their denoising
- **Unet** can be a good candidate for **MR image denoiser**

Methods

Data preparation & overall plan



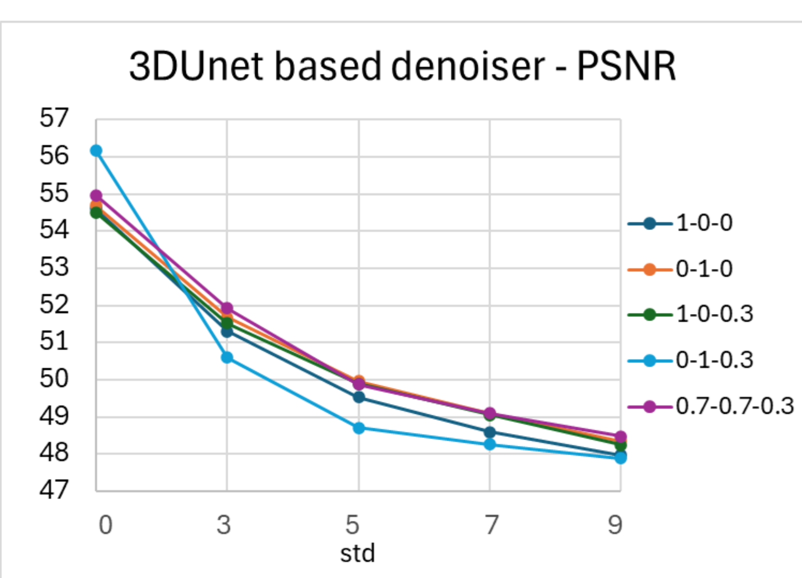


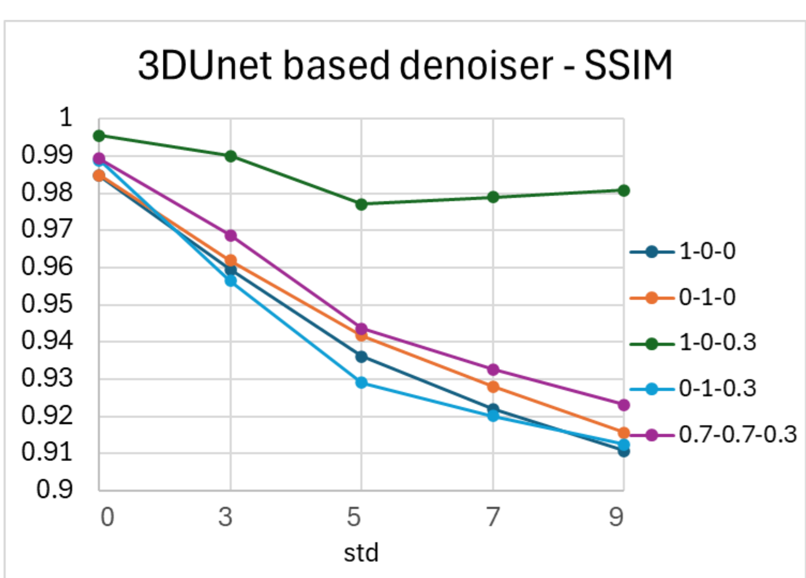
Unet-based denoisers

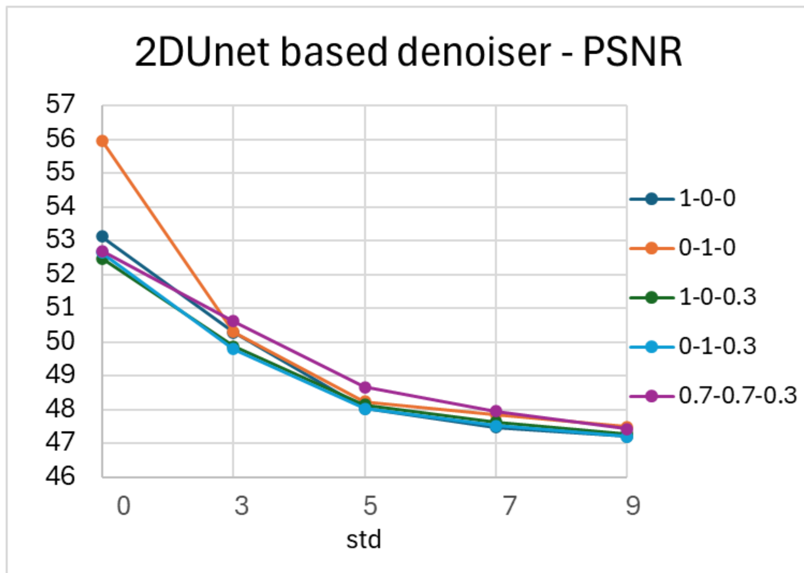
2D Unet Input: batch*176*176	x	L1 loss – L2 loss – SSIM loss 1-0-0 0-1-0 1-0-0.3 0-1-0.3 0.7-0.7-0.3	=	10 Unet-based denoisers
3D Unet Input: batch*176*176*160				

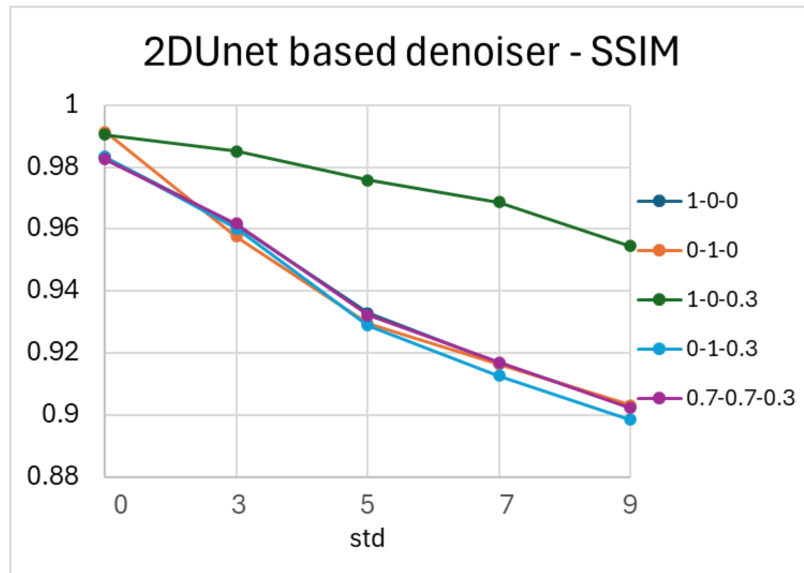
Results

1. Performance of Unet-based denoiser for local field map denoising





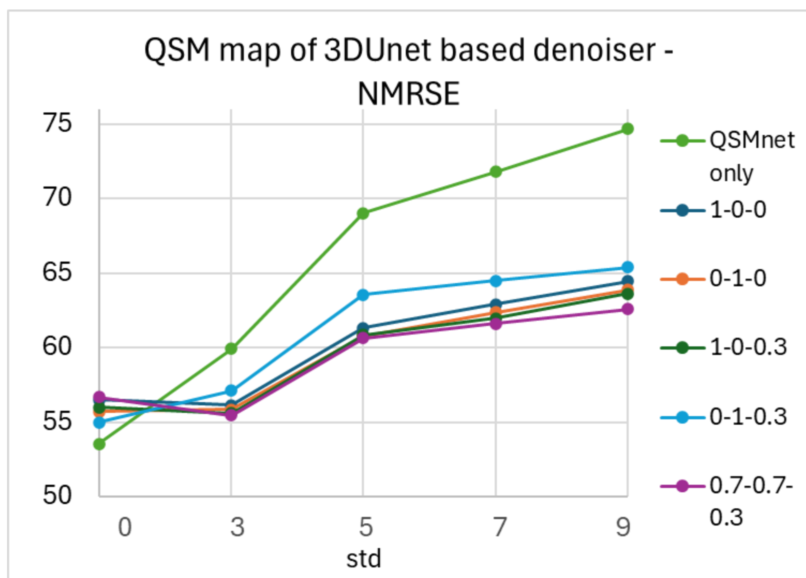


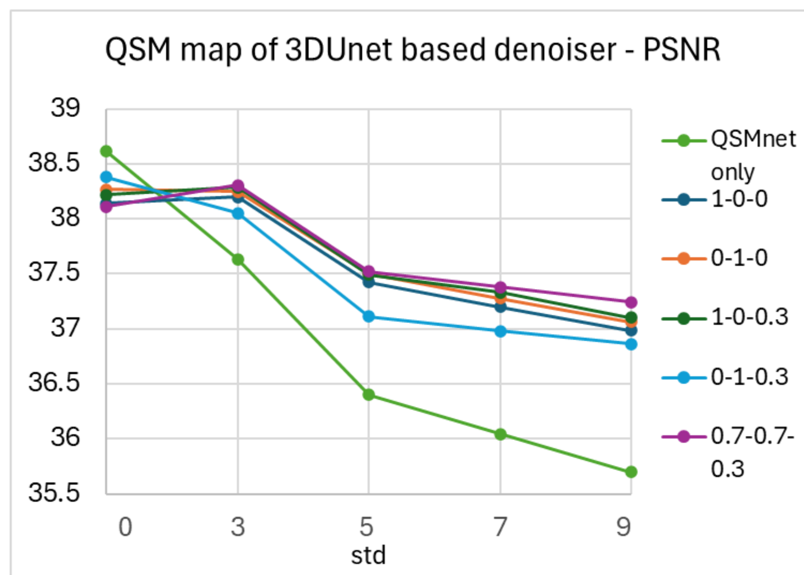


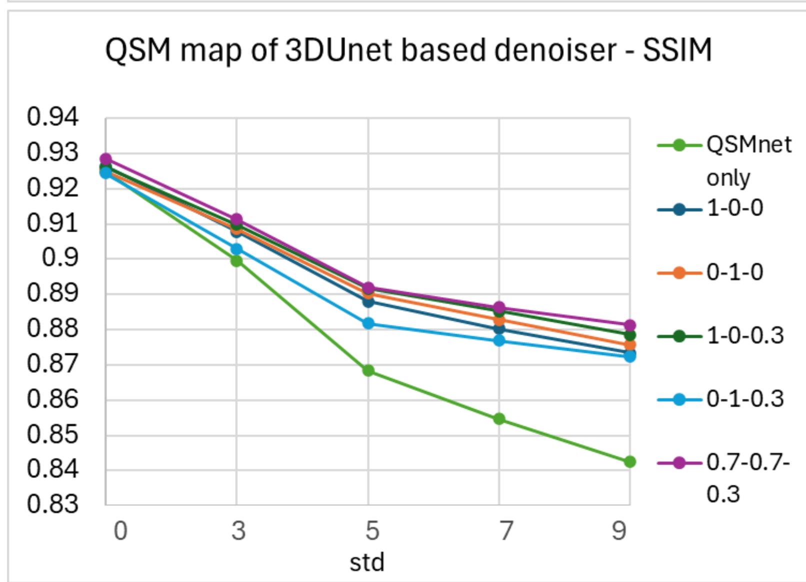
Best model

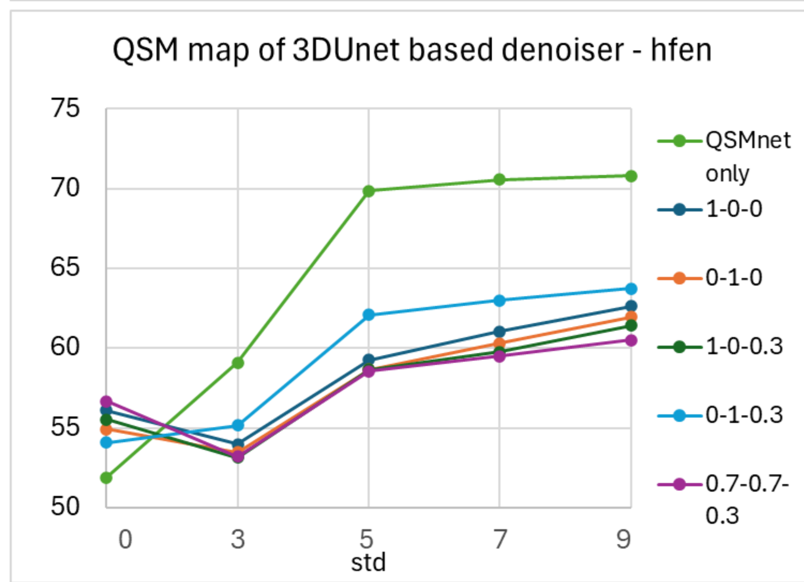
	std0	std3	std5	std7	std9
pSNR	3D, 0-1-0.3	3D, 0.7-0.7-0.3	3D, 0-1-0	3D, 0.7-0.7-0.3	3D, 0.7-0.7-0.3
SSIM	3D, 0-1-0.3	3D, 0-1-0.3	3D, 0-1-0.3	3D, 0-1-0.3	3D, 0-1-0.3

2. Performance of 3D-Unet based cascade model and QSMnet only model for QSM mapping









Best model

	std0	std3	std5	std7	std9
NRMSE	QSMnet_only	1-0-0	1-0-0	1-0-0.3	1-0-0.3
pSNR	QSMnet_only	1-0-0	1-0-0	1-0-0.3	1-0-0.3
SSIM	QSMnet_only	1-0-0.3	1-0-0.3	1-0-0.3	1-0-0.3
hfen	QSMnet_only	1-0-0.3	1-0-0.3	1-0-0.3	1-0-0.3

Conclusion

- 3D Unet-based denoiser was much better than 2D-based denoiser.
- With clean input, denoiser + QSMnet cascade model was worse than using QSMnet alone.
- With artificial noise, 3D Unet-based denoiser with L1 or L1+SSIM loss term produced the best QSM.

References

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