Enhancing Accuracy in Brain Susceptibility Mapping with Unrolling Iterations in χ-sepnet

Kang-wook Kim[1]

[1]Seoul National University

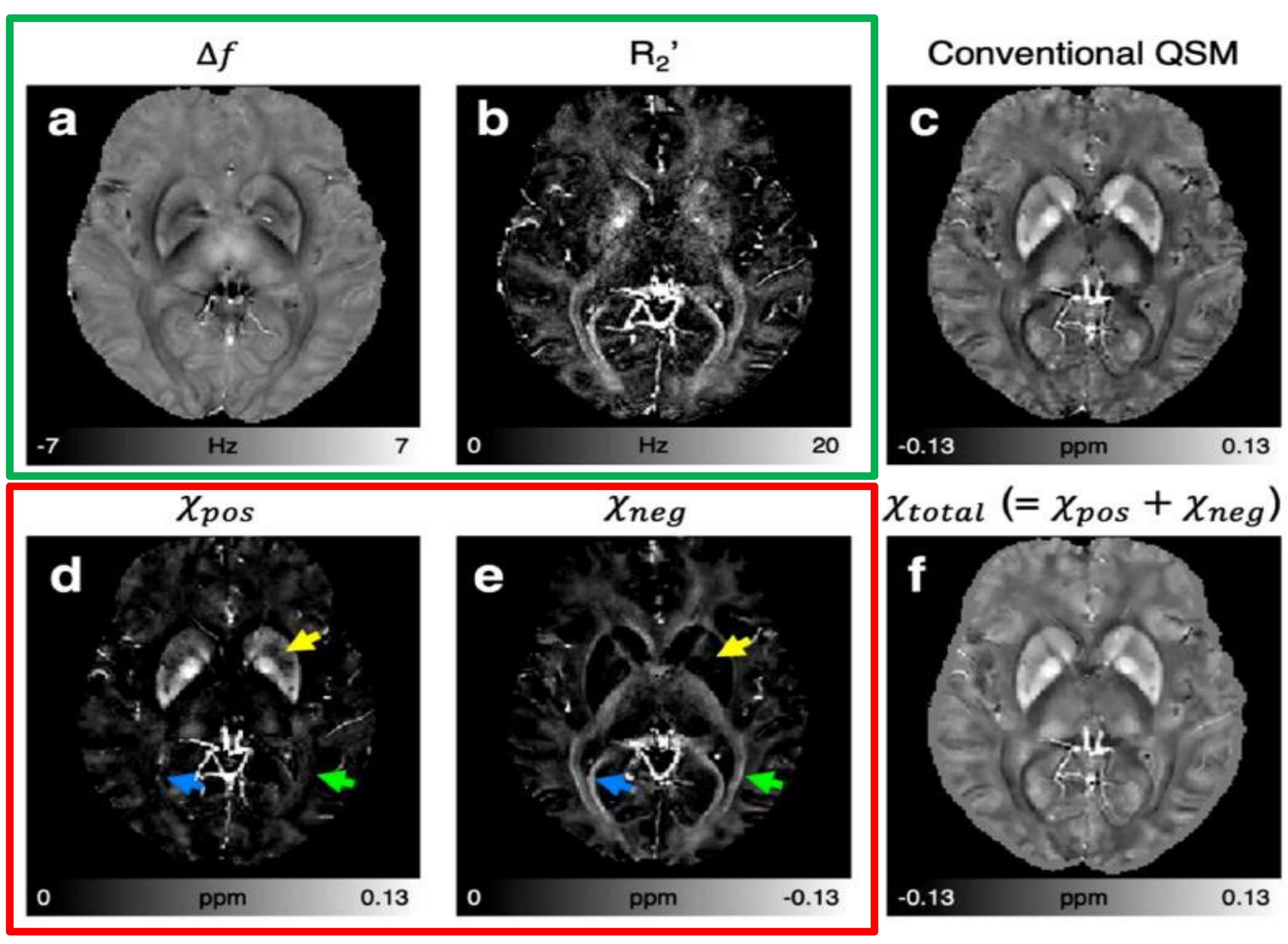
Introduction:

- **χ-separation[1]** introduces a breakthrough in MRI technology, enabling us to distinguish between **paramagnetic and diamagnetic** materials in the brain.
- A limitation of χ-separation is its need for **multiple head orientaions**, leading to **increased scan times** and operational challenges.
- Kim et al.[2] recently developed **χ-sepnet**, a neural network-based solution for estimating χ_{pos} and χ_{neg} maps from **single orientation**.
- This paper explores the use of **unrolling iteration** to boost the performance of **χ-sepnet**, enhancing its accuracy.

Background:

- χ-separation utilizes the **local phase(Δf) and R_2'** brain map as its essential inputs.

Input



Output

- The relationship between output and input is represented as follows:

$$\Delta f(\mathbf{r}) = D_f(\mathbf{r}) * (\chi_{pos}(\mathbf{r}) + \chi_{neg}(\mathbf{r}))$$

$$R_2'(\mathbf{r}) = D_{r,pos} \cdot |\chi_{pos}(\mathbf{r})| + D_{r,neg} \cdot |\chi_{neg}(\mathbf{r})|$$

Methods:

- Since the **physical relationship** between input and output is known, we leverage unrolling iteration to enforce such knowledge into model.

- We can transpose relationship into equation below:

$$y = \Phi x + v$$

, where $y = \begin{bmatrix} Sus \\ R_2' \\ \Delta f \end{bmatrix}, x = \begin{bmatrix} \chi_{pos} \\ \chi_{neg} \end{bmatrix}, \Phi = \begin{bmatrix} I & -I \\ I & I \\ F^{-1}DF & -F^{-1}DF \end{bmatrix}, v = noise.$

F and *D* indicate *Fourier transform* and *dipole kernel*, respectively.

- By following **unrolling iteration** below, our model predicts **(i+1)-th prediction ($\hat{x}_{i+1}$) enhanced from i-th prediction ($\hat{x}_i$)**:

$$\hat{x}_{i+1} = P_\theta\left(\alpha\Phi^H y + (I - \alpha\Phi^H\Phi)\hat{x}_i\right)$$

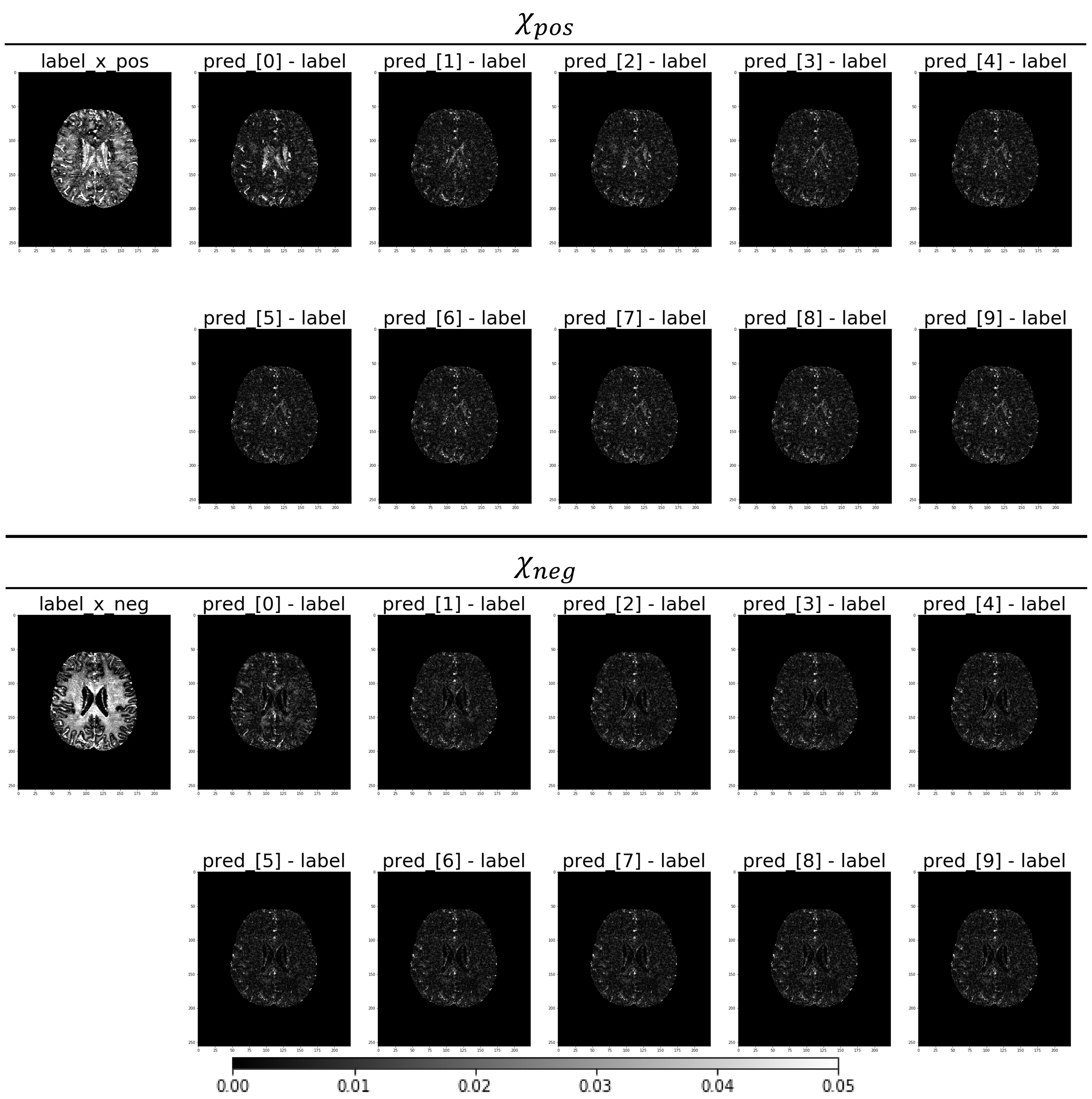
, where P_θ indicates the **neural network**.

- Note that **initial prediction($\hat{x}_0$) is zero** for both χ_{pos} and χ_{neg}.

Experiments:

- Our neural network's design draws inspiration from the U-net model used in χ-sepnet[2], incorporating **10 unrolling iterations** during both training and inference phases.
- We utilize **multi-echo GRE** and **multi-echo SE** data acquired from eight healthy subjects (4:1:3 subjects for train:validation:test)
- We benchmark our model against the established χ-sepnet- R_2'[2].

Results:



χ_{para}	NRMSE(↓)	PSNR(↑)	SSIM(↑)
Baseline χ-sepnet-R_2'	33.72 ± 2.77	47.45 ± 0.94	**0.94322 ± 0.00592**
Unrolled χ-sepnet-R_2'	**33.46 ± 2.83**	**47.52 ± 0.98**	0.94307 ± 0.00600

χ_{dia}	NRMSE(↓)	PSNR(↑)	SSIM(↑)
Baseline χ-sepnet-R_2'	35.79 ± 2.62	48.17 ± 0.70	0.94179 ± 0.00506
Unrolled χ-sepnet-R_2'	**35.33 ± 2.72**	**48.28 ± 0.78**	**0.94246 ± 0.00536**

- Our enhanced version, the **unrolled χ-sepnet- R_2'**, demonstrates **superior performance over the baseline**, achieving **higher scores** in key metrics: **NRMSE, PSNR, and SSIM**.

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References:

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[2] Kim, M., Shin, H. G., Oh, C., Jeong, H., Ji, S., An, H., Kim, J., Jang, J., Bilgic, B., Lee, J. Chi-sepnet: Susceptibility source separation using deep neural network.