



Paper



Slides

Plug-and-Play Priors for Reconstruction-based Placental Image Registration (PnP-RR)

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Brief Intro

- We proposed plug-and-play reconstruction-registration method (PnP-RR), which
 - 1) is a deformable image registration framework for noise-corrupted images
 - 2) can be used on registering placental diffusion-weighted MR images that contains noise



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Contents

1. Background
 - 1) What is image registration and why we need it
 - 2) Why there is noise in the images and the basic idea to deal with it.
2. Related works and their weakness
3. Proposed method: PnP-RR
4. Experiments and results
5. Discussion and conclusion

Background

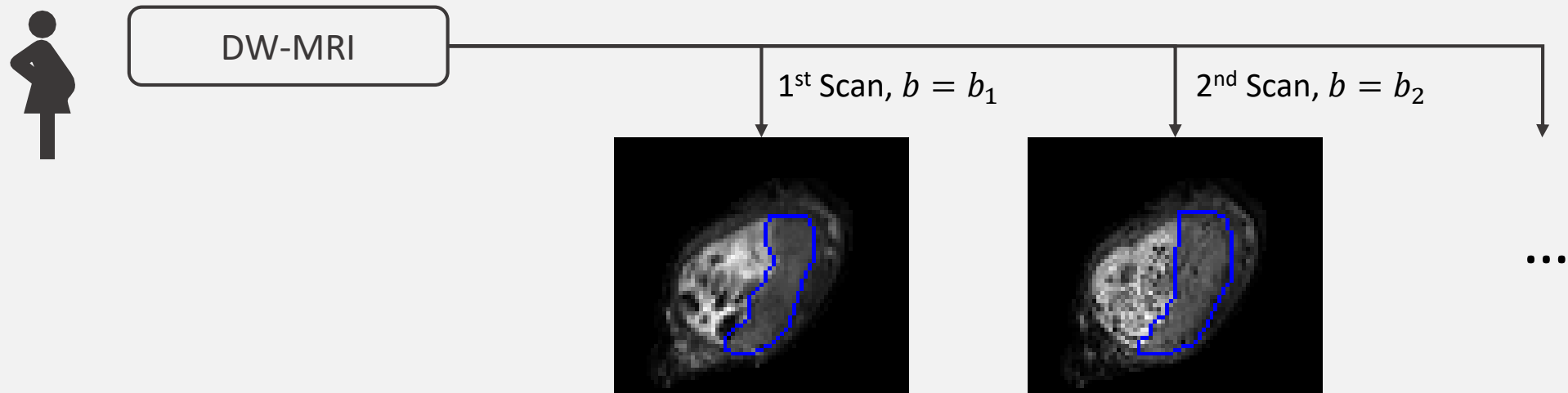
- Placenta and DW-MRI
 - **Diffusion-weighted MRI (DW-MRI)** has recently been used in placental health monitor



Background

- Placenta and DW-MRI

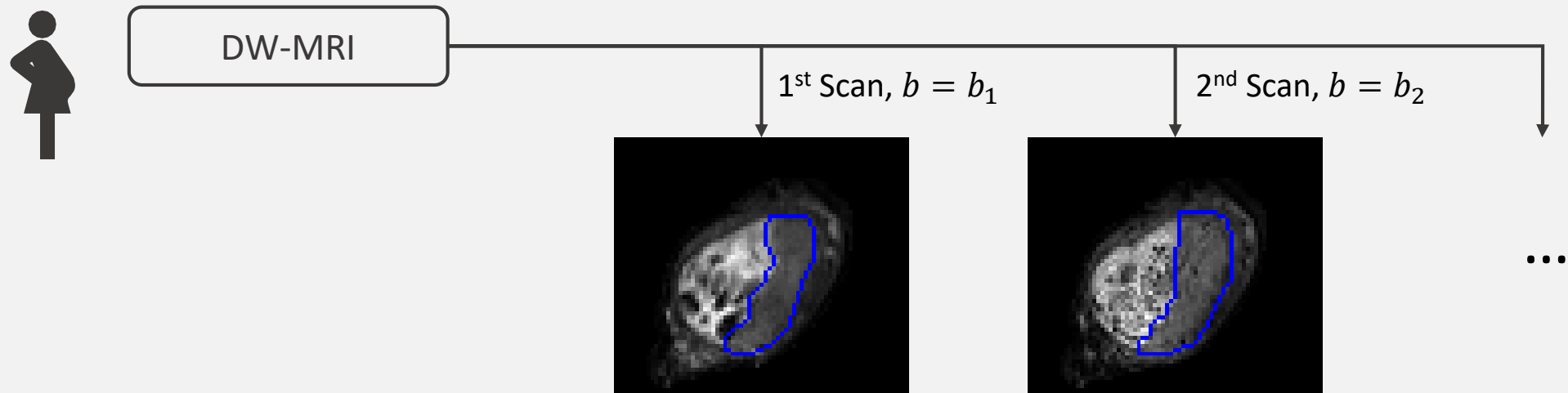
- Diffusion-weighted MRI (DW-MRI) has recently been used in placental health monitor
- We need to collect **several placental DW-MR images** with **different parameters** (b-values) and track how the look of placenta changes with different b-value



Background

- Placenta and DW-MRI

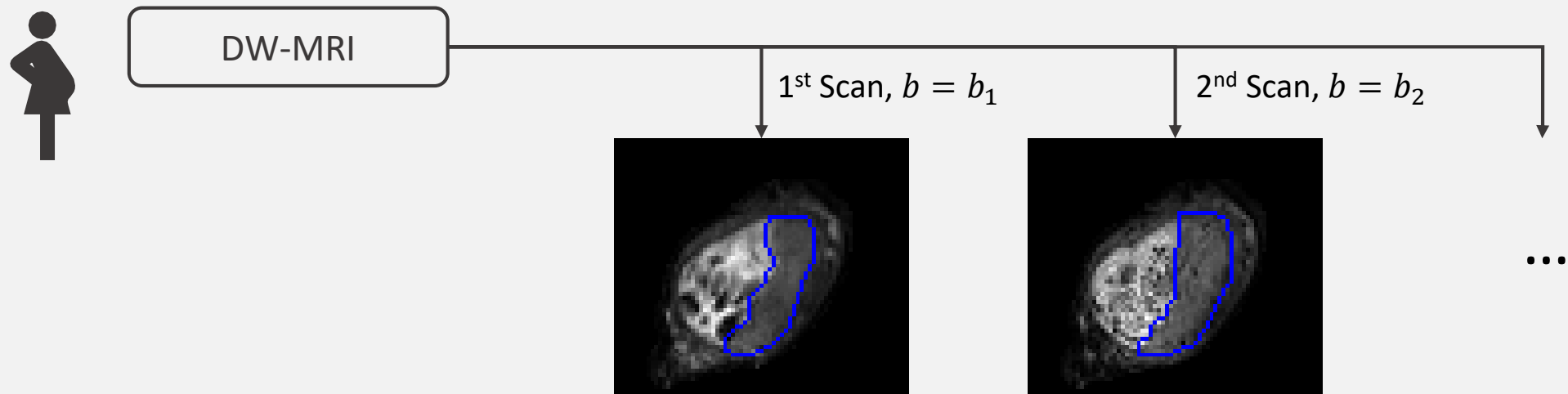
- Diffusion-weighted MRI (DW-MRI) has recently been used in placental health monitor
- We need to collect several placental DW-MR images with different parameters (b-values) and track how the look of placenta changes with different b-value
- However, due to **maternal breathing and fetal movements**, there would be **deformation among the images**, make it hard to track the change



Background

- Placenta and DW-MRI

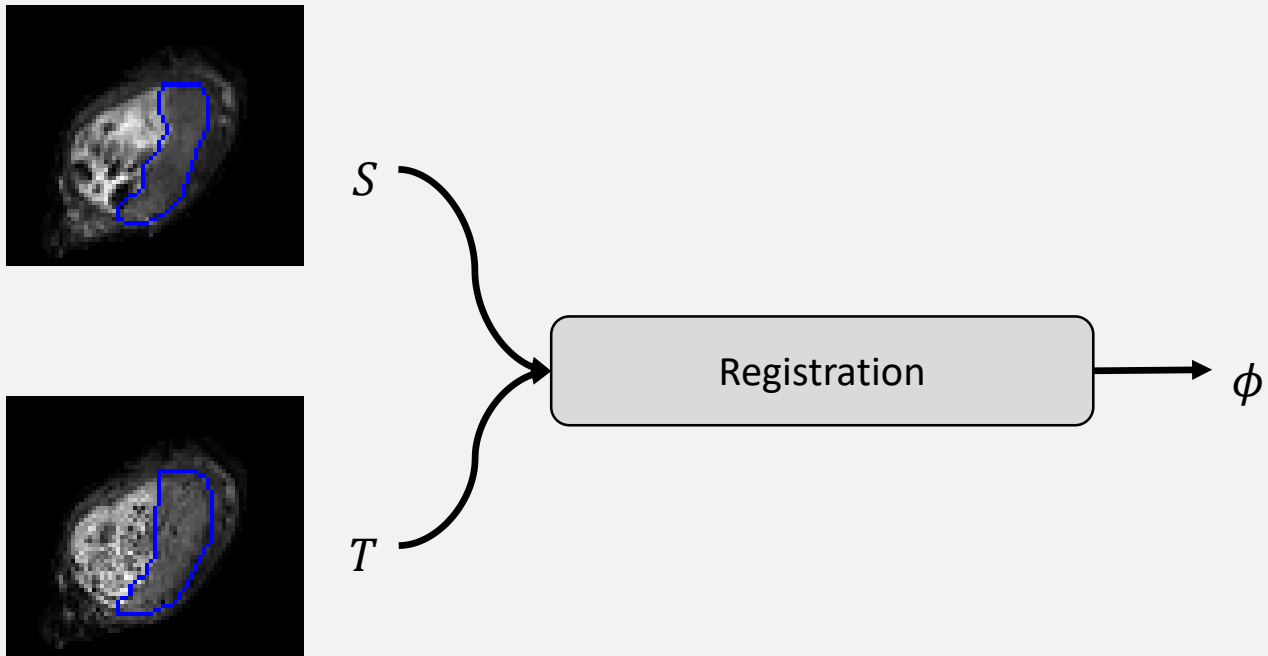
- Diffusion-weighted MRI (DW-MRI) has recently been used in placental health monitor
- We need to collect several placental DW-MR images with different parameters (b-values) and track how the look of placenta changes with different b-value
- However, due to breath and movement, there would be deformation among the images, make it hard to track the change
- Therefore, **image registration** is needed to **find and cancel the deformation** and align the placenta in images.



Background

- Image Registration

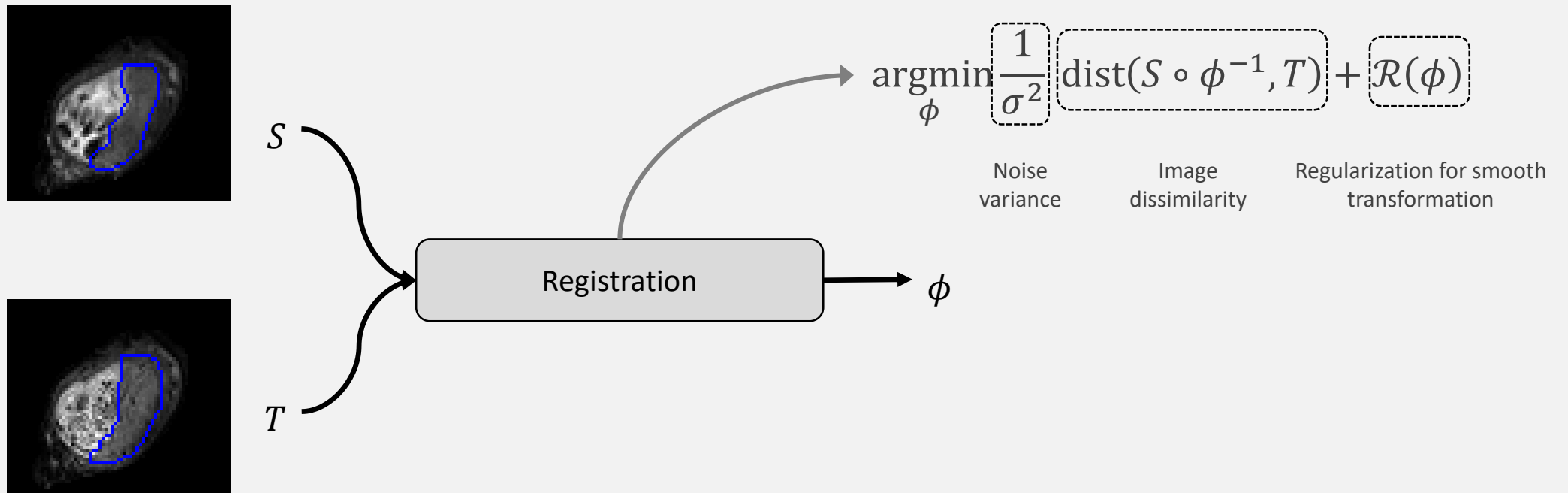
- Task: find the deformation ϕ between a source Image S and a target image T



Background

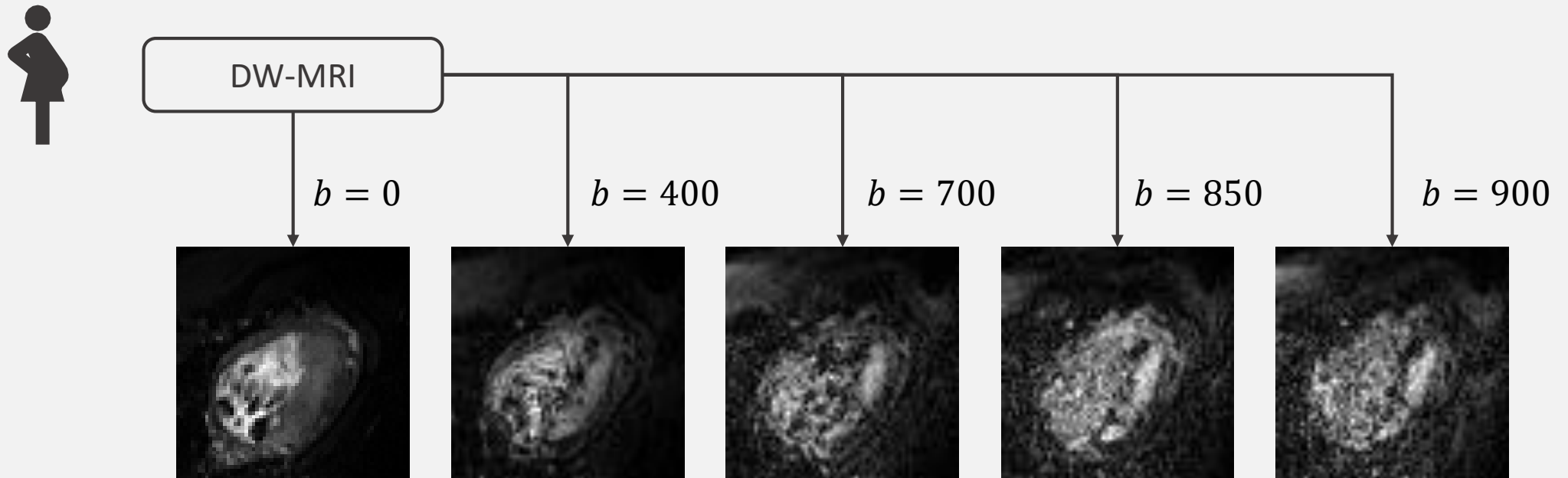
- Image Registration

- Task: find the deformation ϕ between a source Image S and a target image T
- Current mainstream: optimization-based methods
 - take the deformation that minimize an energy function



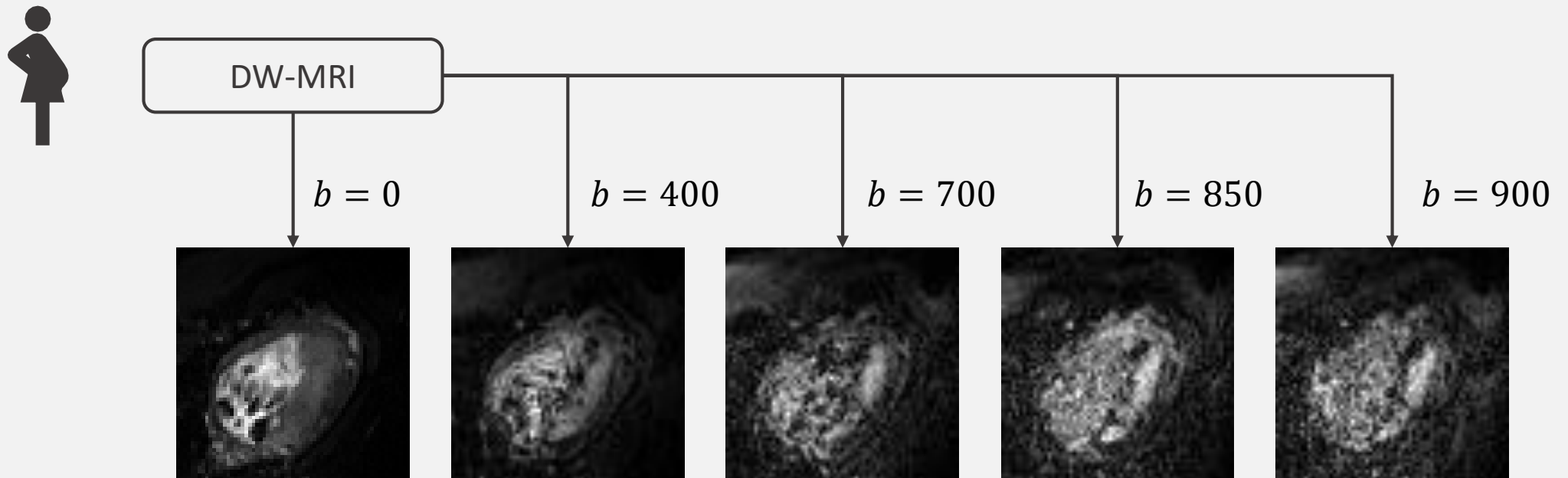
Background

- B-value and noise
 - Assumption of ordinary registration method: deformation is the only difference

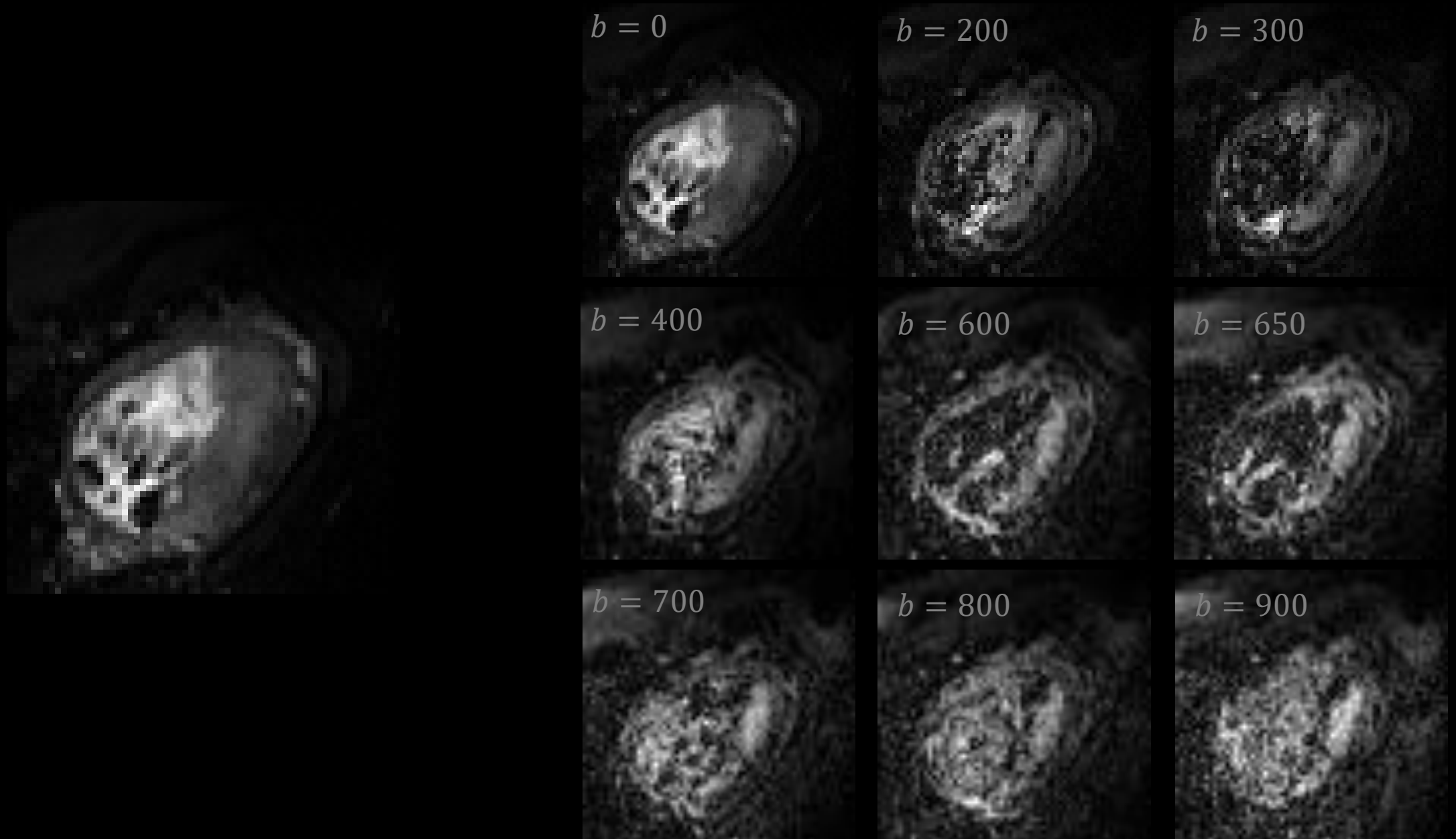


Background

- B-value and noise
 - Assumption of ordinary registration method: deformation is the only difference
 - However, higher b-value, stronger noise

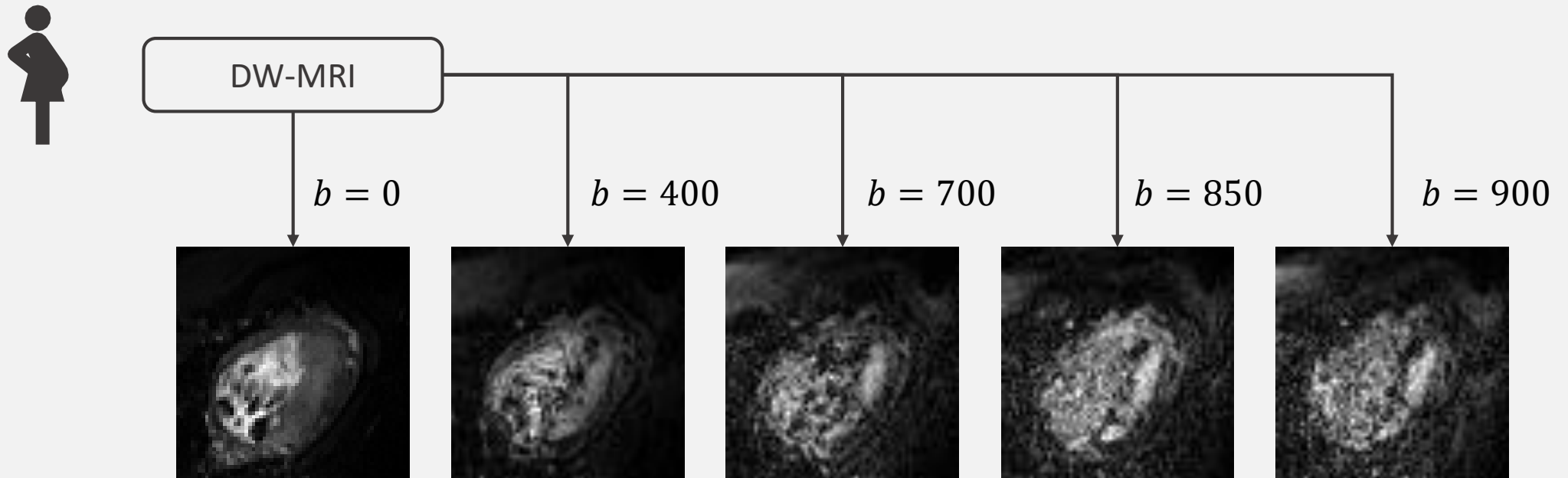


DW-MR image from same location in different b-values



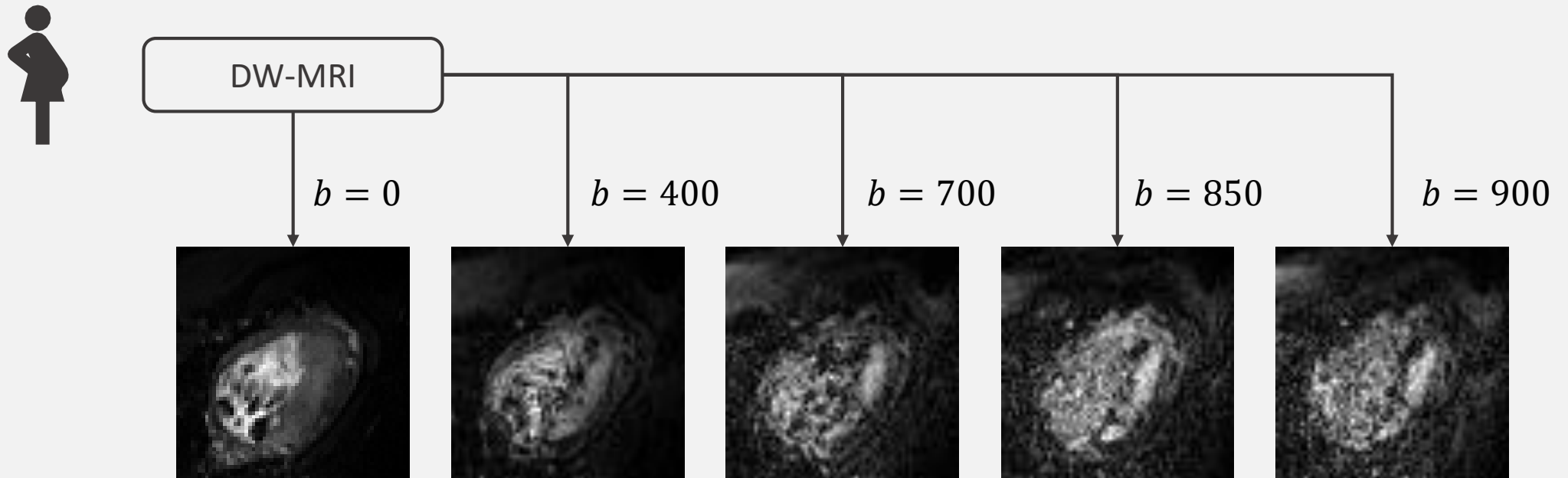
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Background

- B-value and noise
 - Assumption of ordinary registration method: deformation is the only difference
 - However, higher b-value, stronger noise
 - Ordinary registration methods fail
 - A noise-robust image registration methods is needed



Related Works

- Basic idea: denoising + registration
 - find a method to combine image denoising and image registration.
 - Image denoising
 - Example: TV denoising for white Gaussian noise



Original



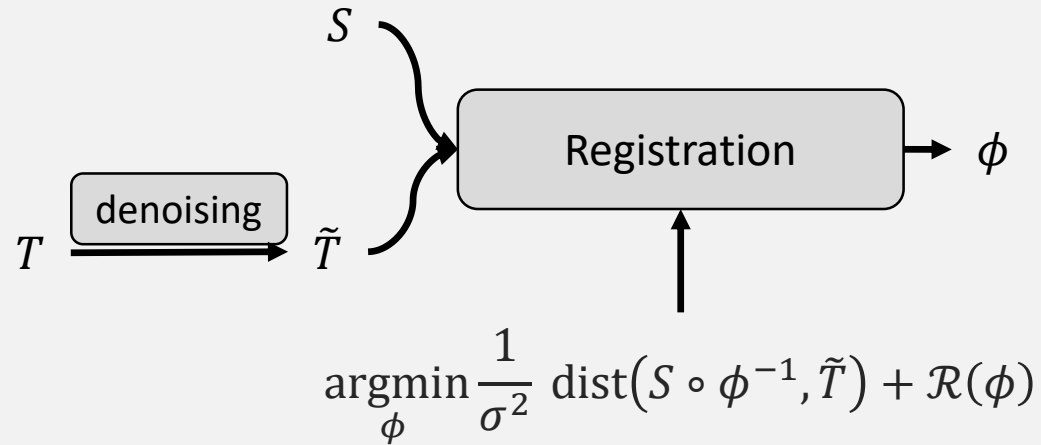
Noisy Image



Denoised image

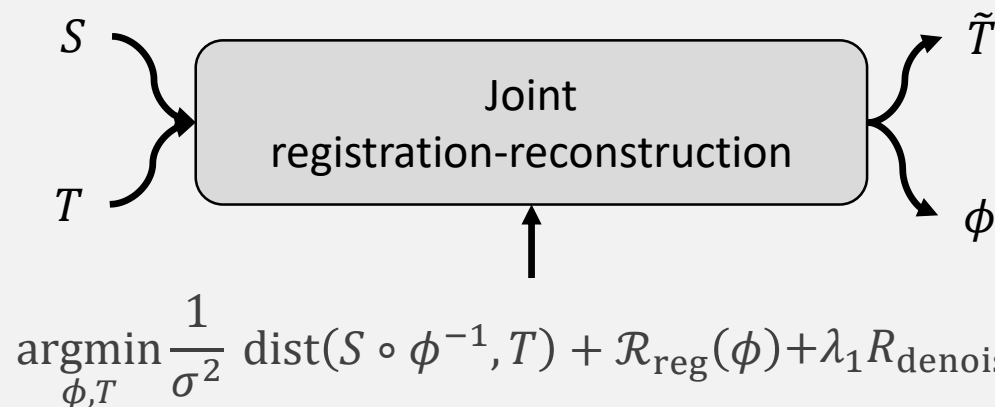
Related Works

- 2-Steps Method: denoising before registration



May **NOT** converge to **OPTIMAL** solution

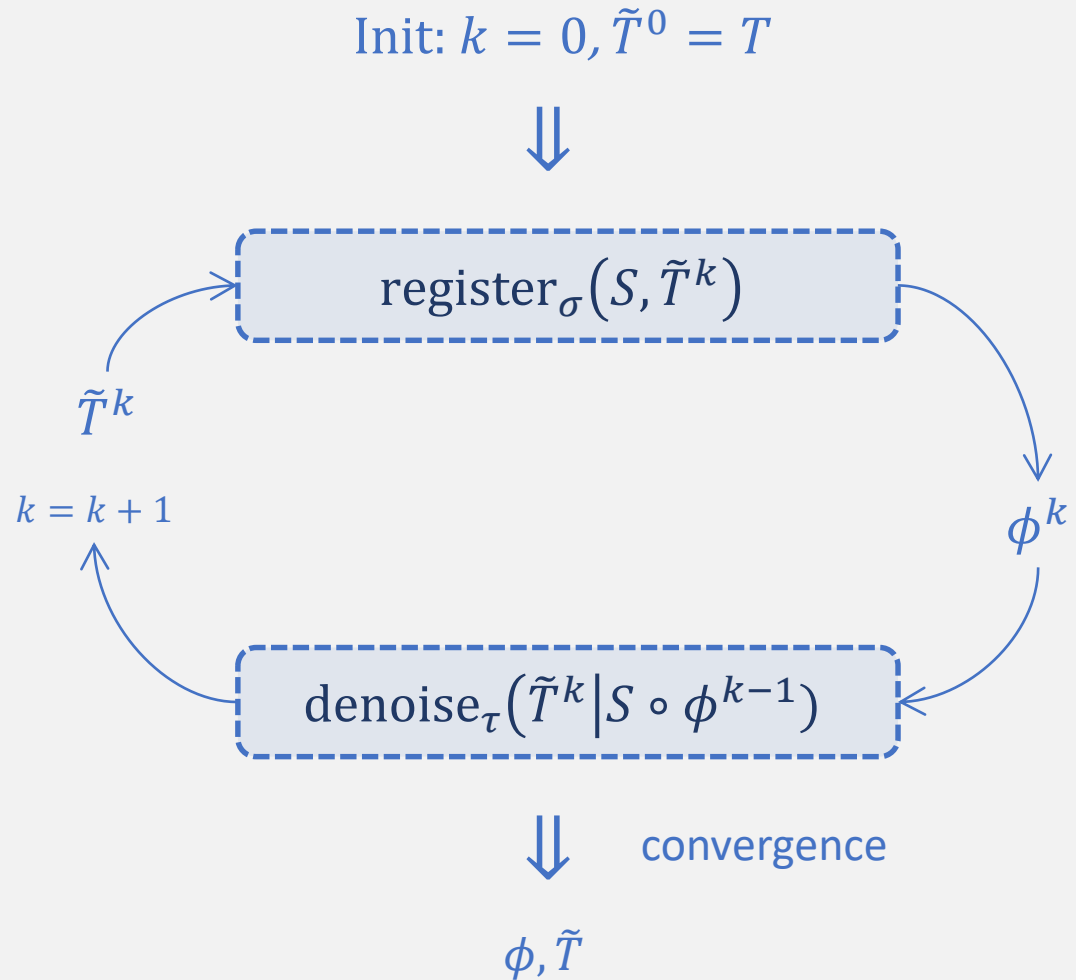
- Joint Optimization Method



Requires explicit objective function;
-> **LIMITED CHOICES** for denoisers

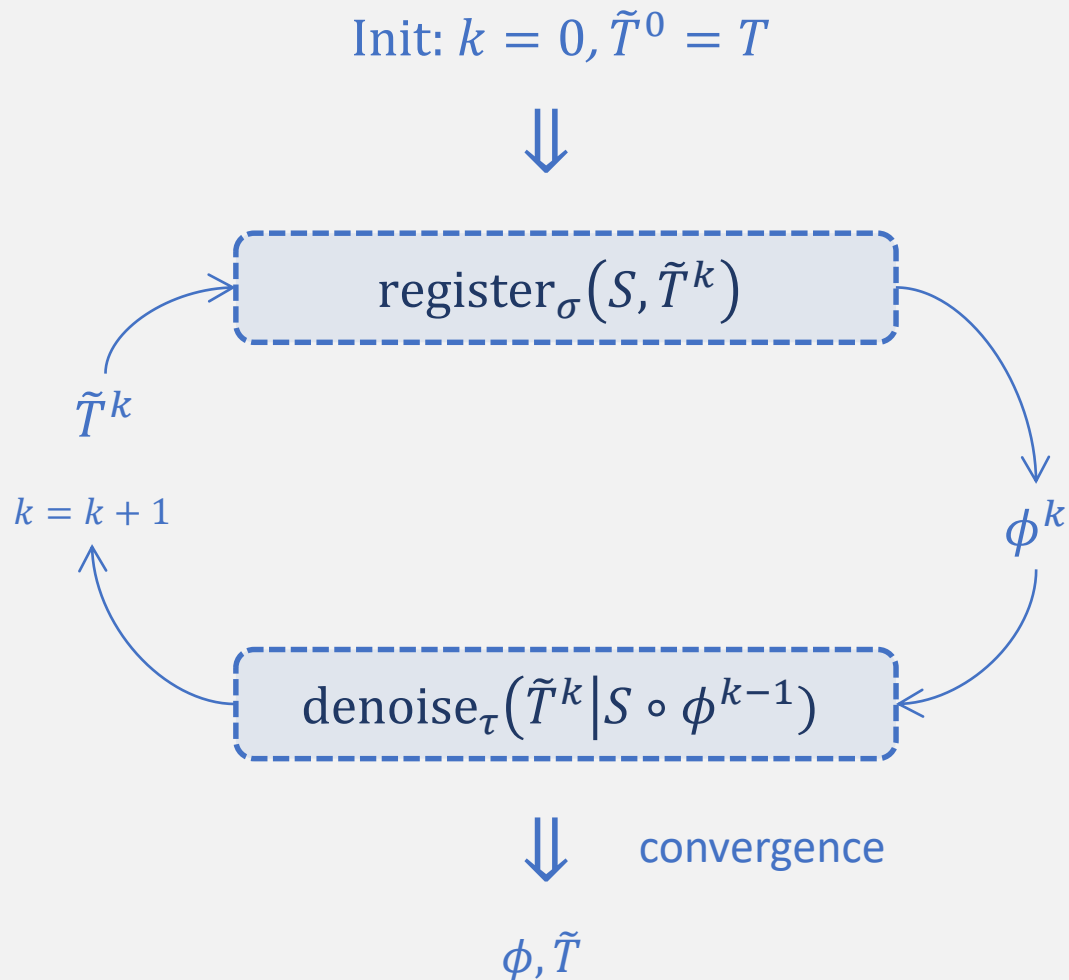
Proposed method: PnP-RR

- Basic Idea



Proposed method: PnP-RR

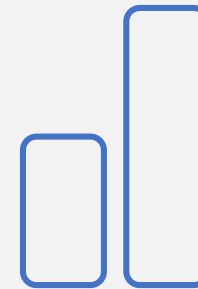
- Basic Idea



- Advantages

- ☐ TV ✓
- ☐ TGV ✓
- ☐ BM3D ✓
- ☐ Neural Network ✓

Flexible to
CHOOSE DENOISER



Better
PERFORMANCE



Simple to
IMPLEMENT



Easy to
TUNE

Proposed method: PnP-RR

- Derivation
 - **JOINT** denoising-registration objective function

$$\operatorname{argmin}_{\phi, \tilde{T}} \frac{1}{\sigma^2} \|S \circ \phi^{-1} - \tilde{T}\|_{L2}^2 + \mathcal{R}_{\text{reg}}(\phi) + \lambda_1 \mathcal{R}_{\text{denoising}}(\tilde{T}) + \lambda_2 \|T - \tilde{T}\|_{L2}^2$$

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- **SPLIT** Formulated as proximal algorithm

$$\begin{aligned} \operatorname{argmin}_{\tilde{T}} \frac{1}{2} \|\tilde{T} - Z\|_{L2}^2 + \tau \mathcal{R}_{\text{denoising}}(\tilde{T}) &= \text{denoise}_{\sigma}(\tilde{T} | S \circ \phi^{-1}) \quad \text{where} \quad Z = \frac{\lambda_2 T + (1/\sigma^2)(S \circ \phi^{-1})}{\lambda_2 + (1/\sigma^2)} \\ \operatorname{argmin}_{\phi} \frac{1}{\sigma^2} \|S \circ \phi^{-1} - \tilde{T}\|_{L2}^2 + \mathcal{R}_{\text{reg}}(\phi) &= \text{register}_{\sigma}(S, \tilde{T}^k) \quad \tau = \frac{\lambda_1}{2(\lambda_2 + (1/\sigma^2))} \end{aligned}$$

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- **REPLACE** Formulated as PnP algorithm

$\text{denoise}'_{\tau}(Z)$

$\text{register}_{\sigma}(S, \tilde{T}^k)$

Proposed method: PnP-RR

- Derivation
 - **JOINT** denoising-registration objective function

$$\operatorname{argmin}_{\phi, \tilde{T}} \frac{1}{\sigma^2} \|S \circ \phi^{-1} - \tilde{T}\|_{L2}^2 + \mathcal{R}_{\text{reg}}(\phi) + \lambda_1 \mathcal{R}_{\text{denoising}}(\tilde{T}) + \lambda_2 \|T - \tilde{T}\|_{L2}^2$$

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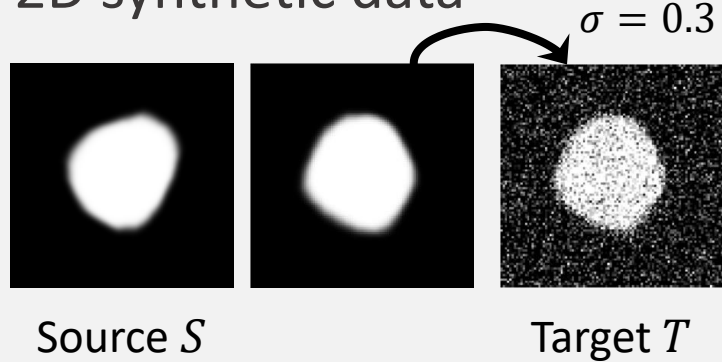
$\text{register}_{\sigma}(S, \tilde{T}^k)$

Specifying an image prior

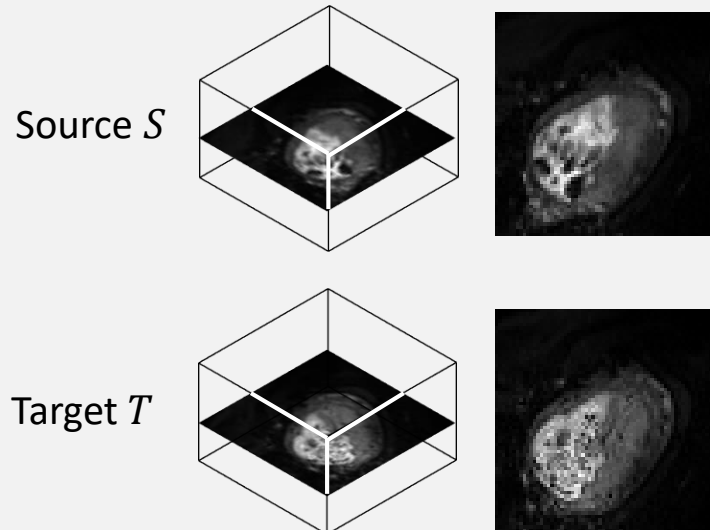
Experiments

- Data

- 2D synthetic data



- Real 3D DW-MRI data



- Algorithm Setting

- Registration algorithm

- Fourier-approximated Lie Algebras for Shooting (FLASH)^[1]

- Denoising algorithm

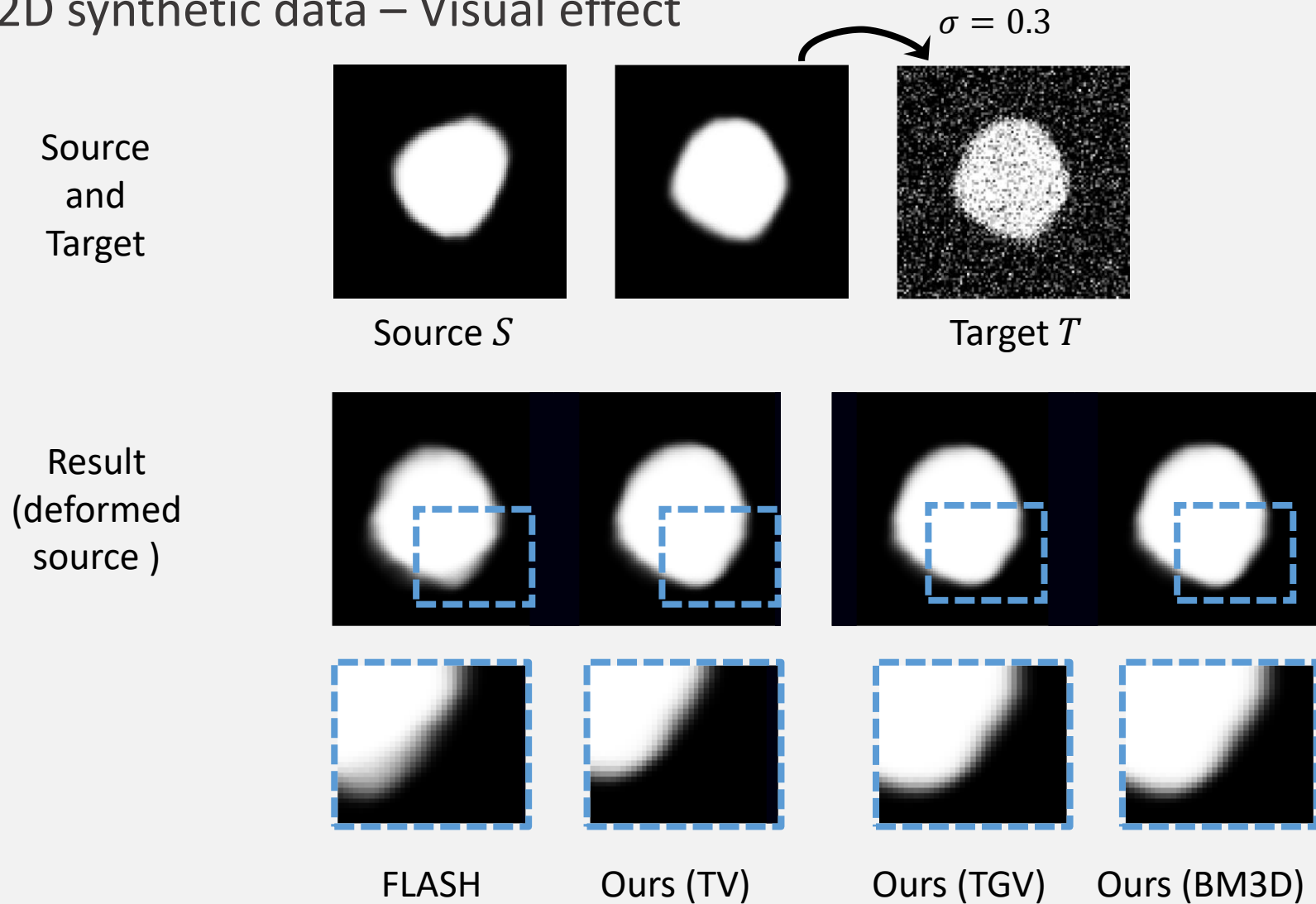
- Total variation (TV)
 - Total generalized variation (TGV)
 - Block-matching and 3D filtering (BM3D)

[1] Zhang, M., Liao, R., Dalca, A.V., Turk, E.A., Luo, J., Grant, P.E., Golland, P.: Frequency diffeomorphisms for efficient image registration. In: International conference on information processing in medical imaging. pp. 559–570. Springer (2017)

Experiments

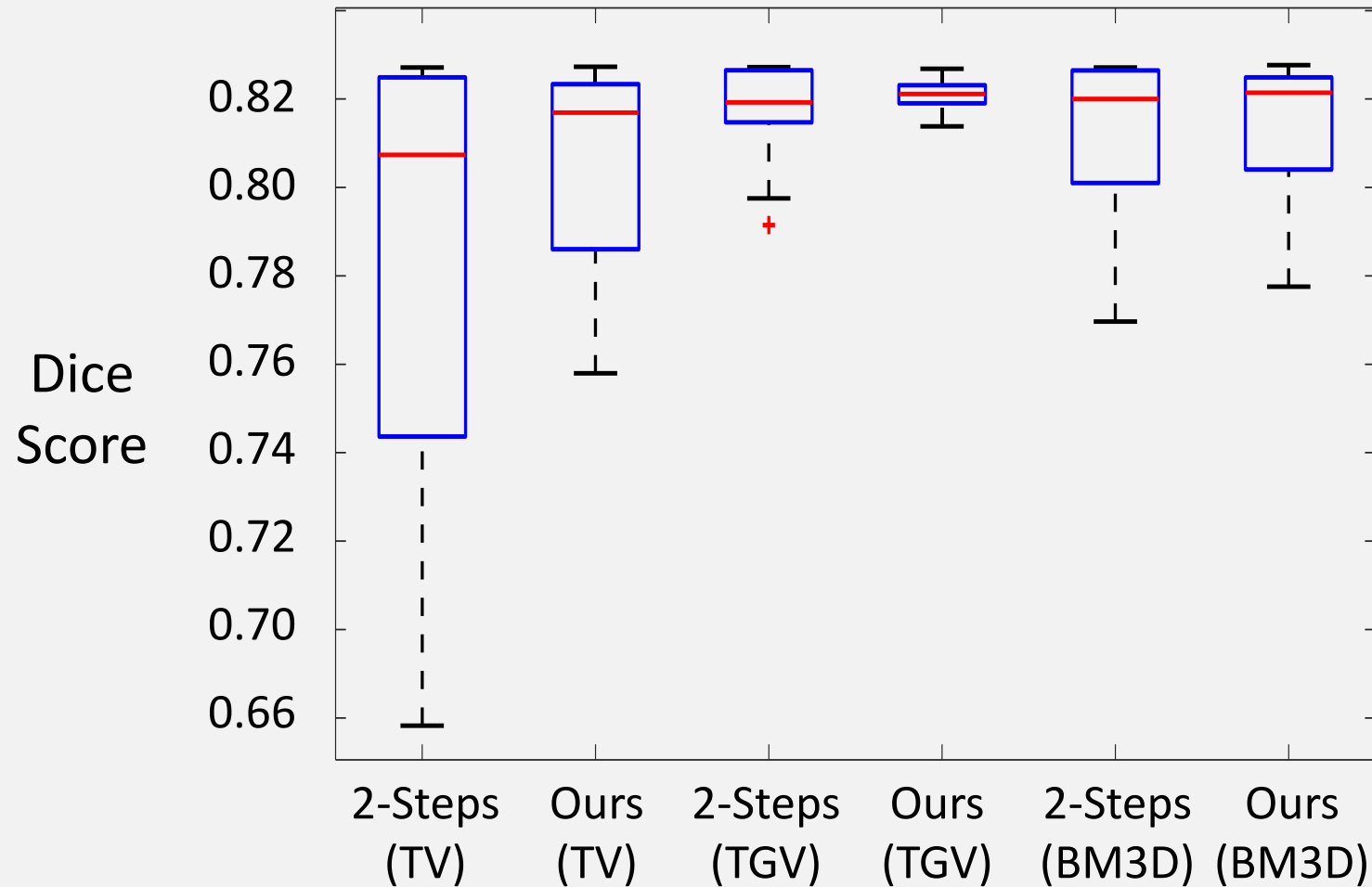
- Result

- 2D synthetic data – Visual effect



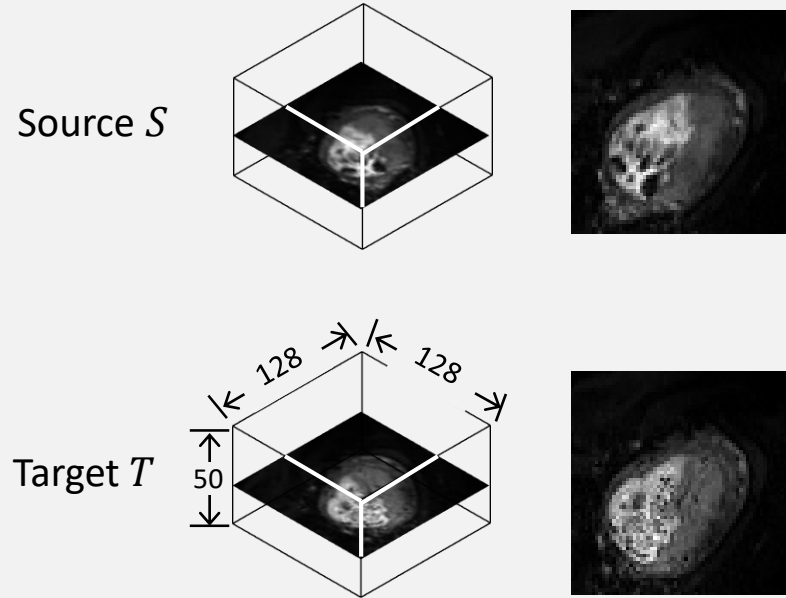
Experiments

- Result
 - 2D synthetic data – Quantitative performance



Experiments

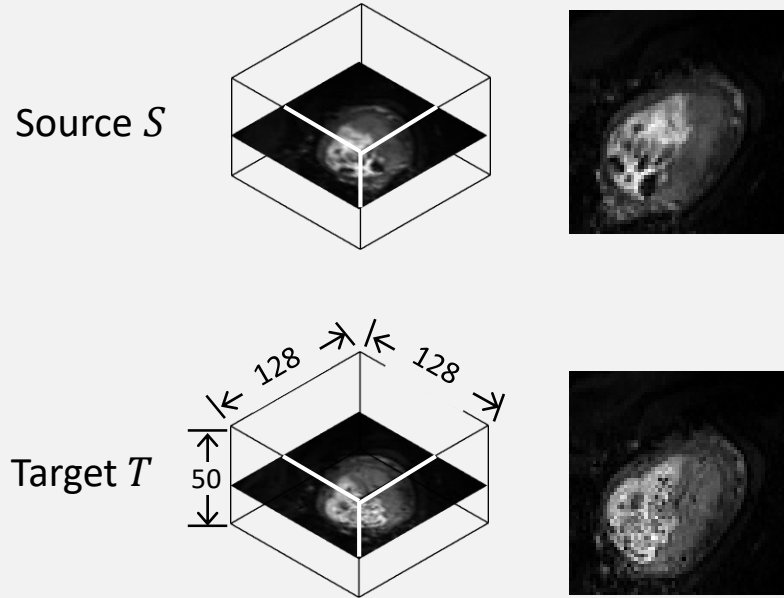
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 - Real 3D DW-MRI data



All DW-MRIs are of dimension $128 \times 128 \times 50$ and underwent bias field correction, co-registration with affine transformations and intensity normalization

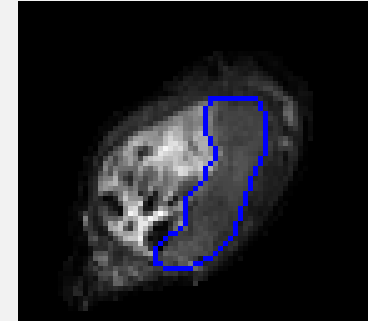
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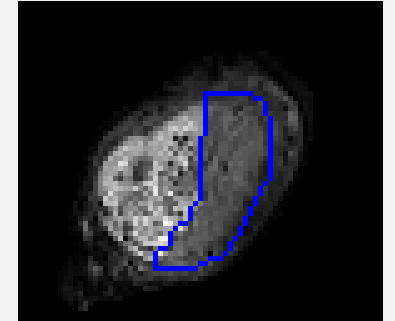


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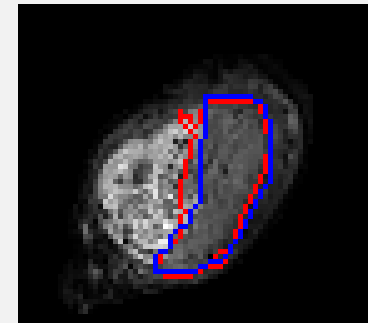
- Result



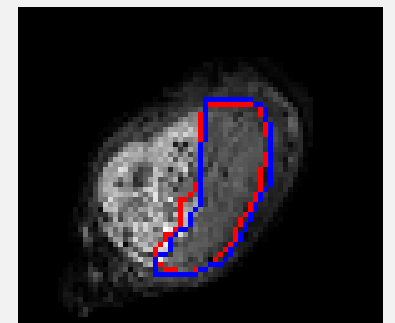
Source



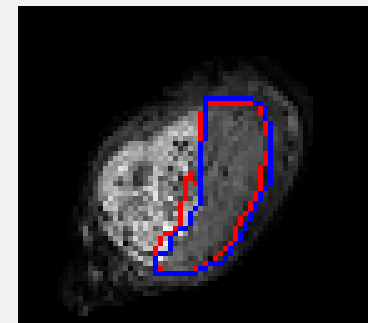
Target



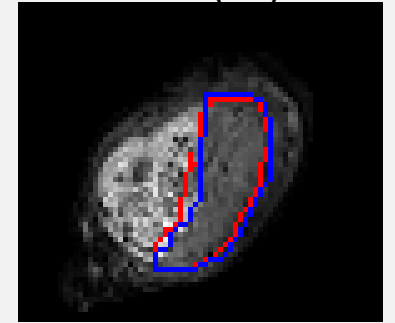
FLASH



Ours (TV)



Ours (TGV)



Ours (BM3D)

Discussion

- Performance
 - Data
 - Advanced methods
- Convergence
- Time

Conclusion

- We presented a novel reconstruction-based registration algorithm, named PnP-RR, for severely noise-corrupted images

Our Team



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Conclusion

- We presented a novel reconstruction-based registration algorithm, named PnP-RR, for severely noise-corrupted images
- In contrast to previous approaches, our model has the flexibility to allow arbitrary denoising algorithm integrated with the registration task
- What's more, our model benefits from its easiness to implement, robustness to parameter tuning and better performance
- Future research will involve collecting more dataset on placental images and exploring other cutting-edge denoisers, such as deep learning-based approaches.
- Questions?

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