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

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Paper

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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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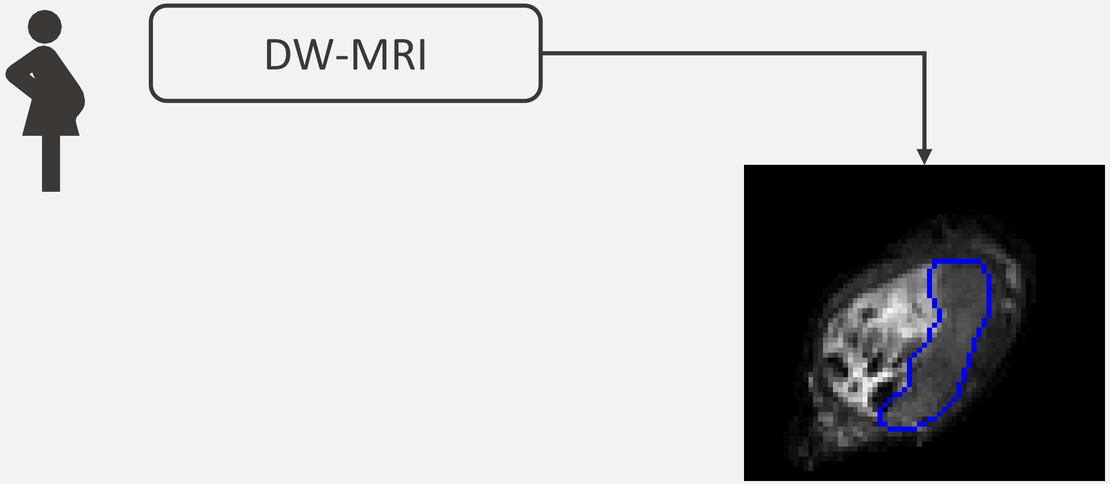
Contents

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

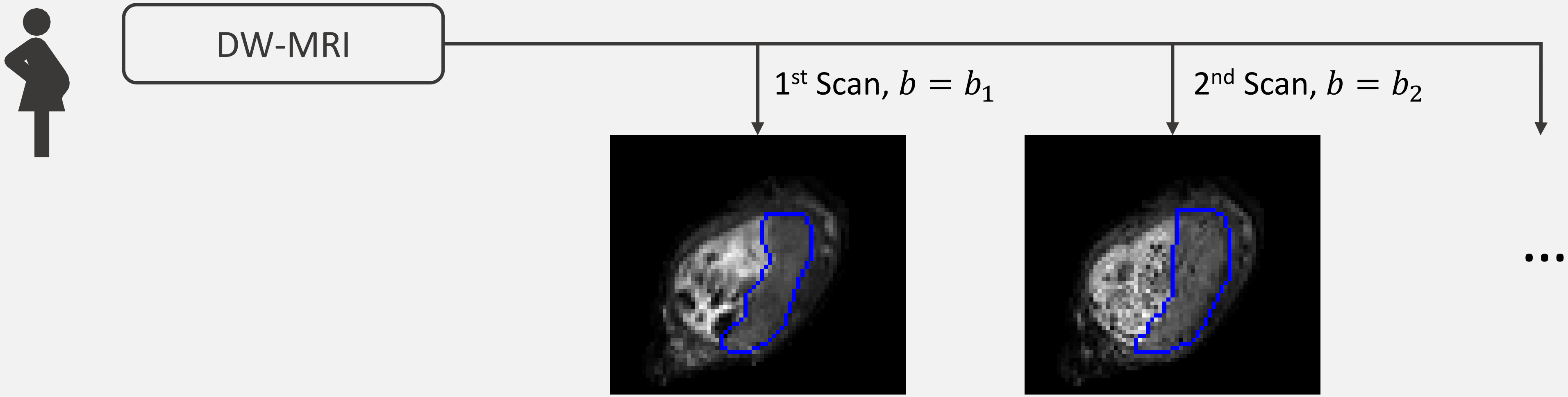
Background

- 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



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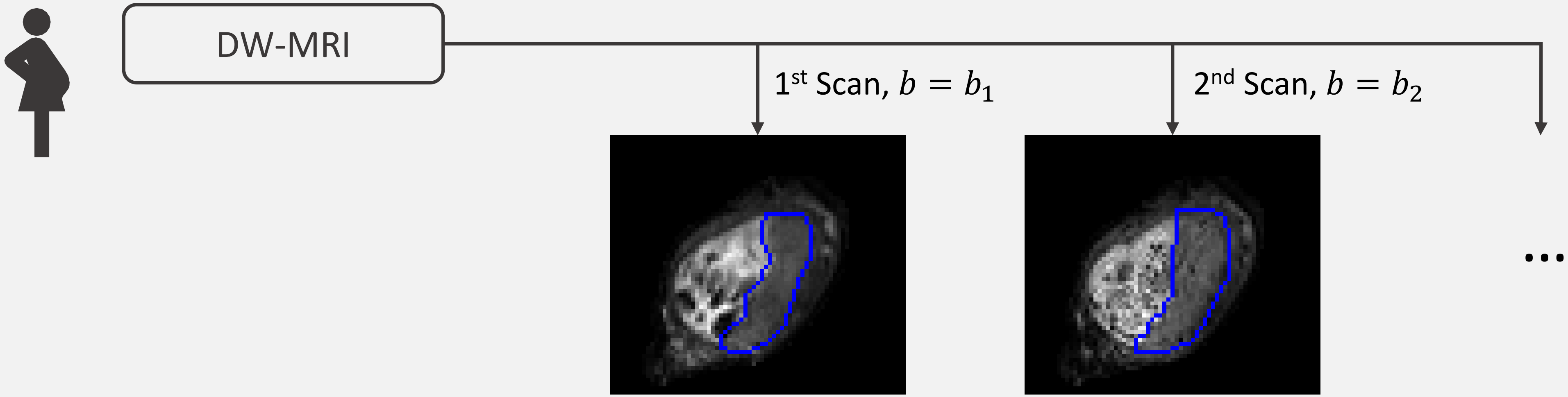
  - Diffusion-weighted MRI (DW-MRI) has recently been used in placental health monitor
  - We need to collect several placental DW-MR images with different parameters (b-values) and track how the look of placenta changes with different b-value
  - However, due to **maternal breathing and fetal movements**,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



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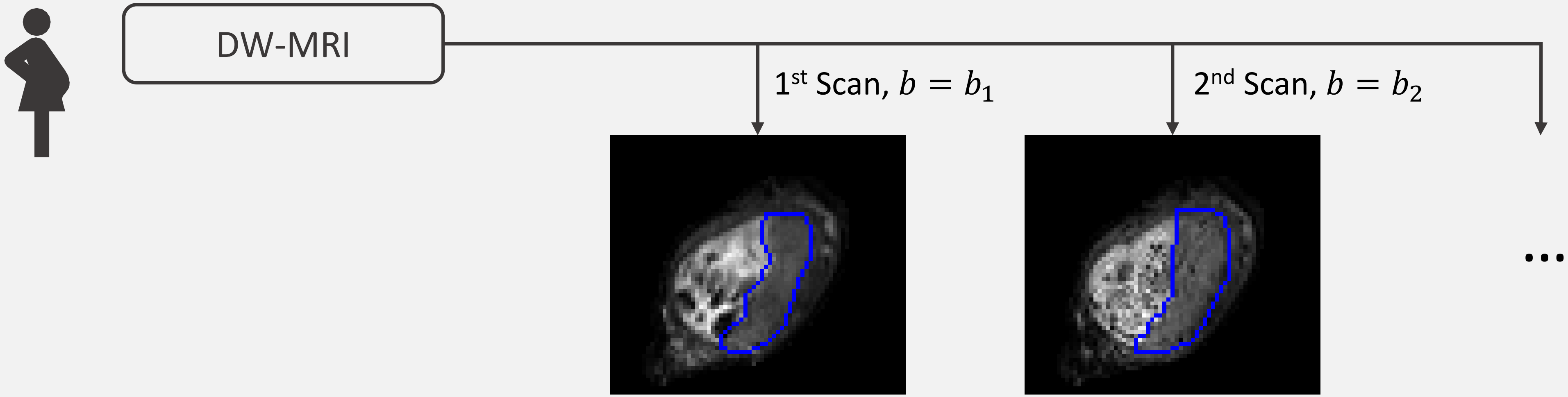
  - Diffusion-weighted MRI (DW-MRI) has recently been used in placental health monitor
  - We need to collect several placental DW-MR images with different parameters (b-values) and track how the look of placenta changes with different b-value
  - However, due to breath and movement, there would be deformation 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.



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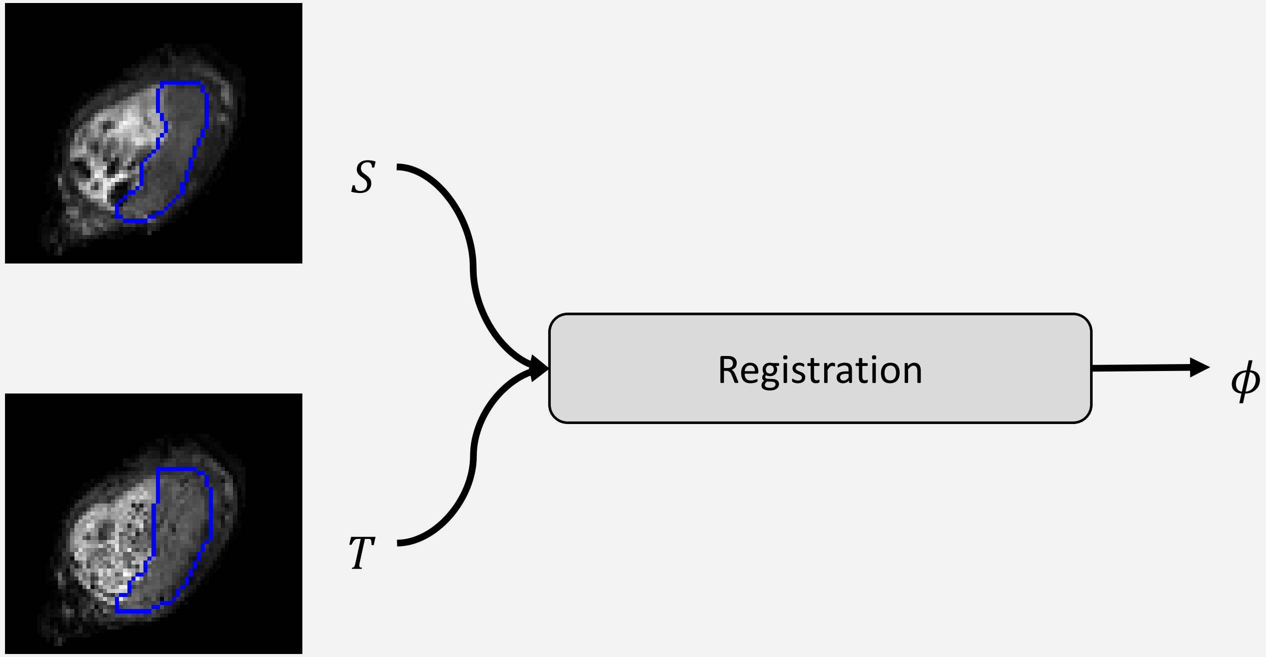
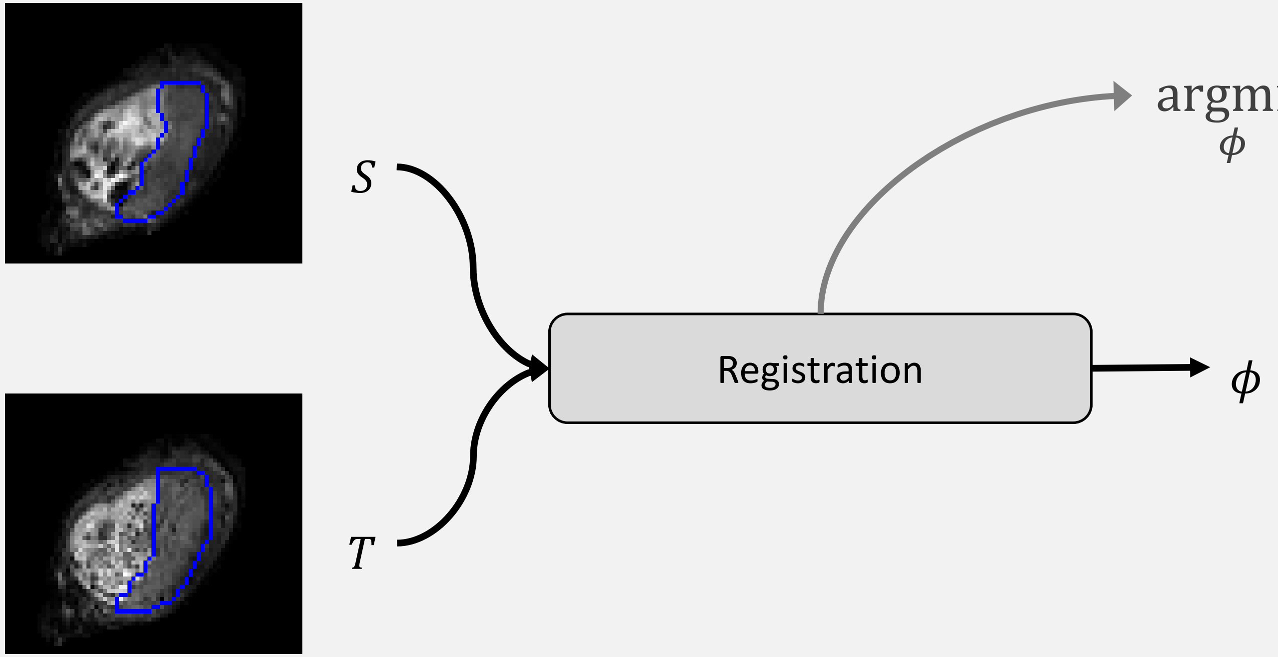
- Image Registration
  - Task: find the deformation ϕ between a source Image S and a target image T



Background

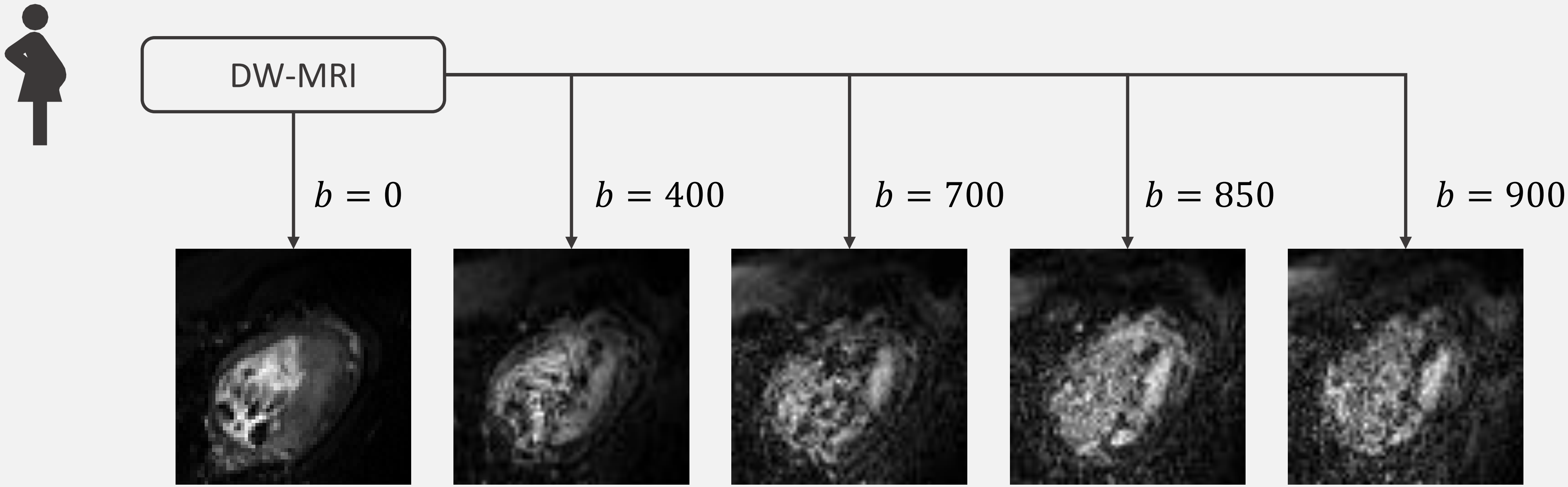
- Image Registration
  - Task: find the deformation ϕ between a source Image S and a target image T
  - Current mainstream: optimization-based methods
    - take the deformation that minimize an energy function



$$\underset{\phi}{\operatorname{argmin}} \underbrace{\boxed{\frac{1}{\sigma^2}}}_{\text{Noise variance}} \underbrace{\boxed{\mathrm{dist}(S \circ \phi^{-1}, T)}}_{\text{Image dissimilarity}} + \underbrace{\boxed{\mathcal{R}(\phi)}}_{\text{Regularization for smooth transformation}}$$

Background

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



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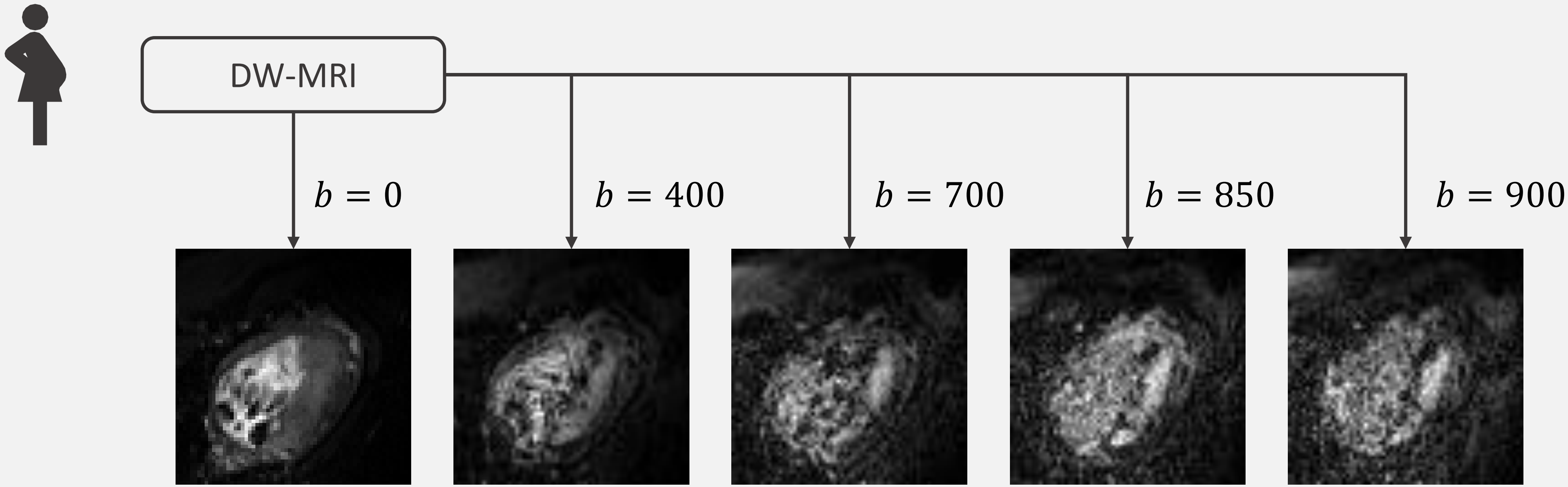
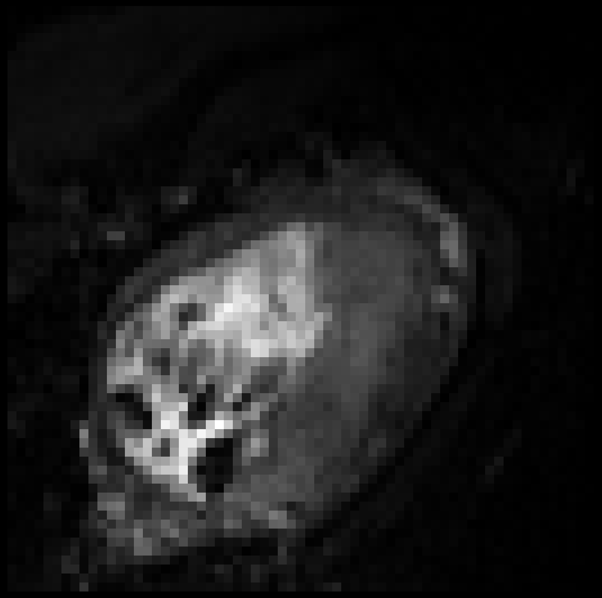
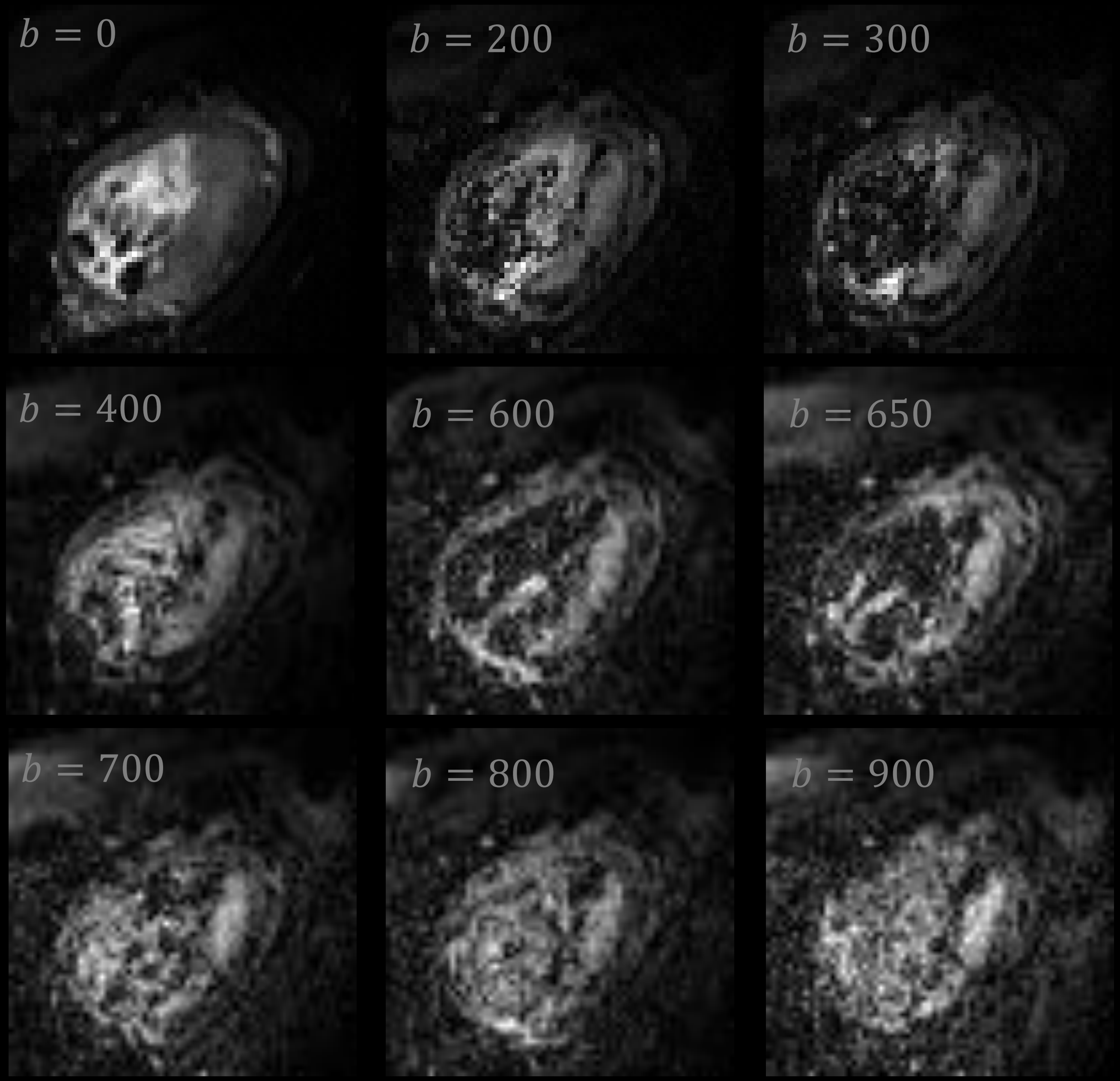
- B-value and noise
  - Assumption of ordinary registration method: deformation is the only difference
  - However, higher b-value, stronger noise



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





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- B-value and noise
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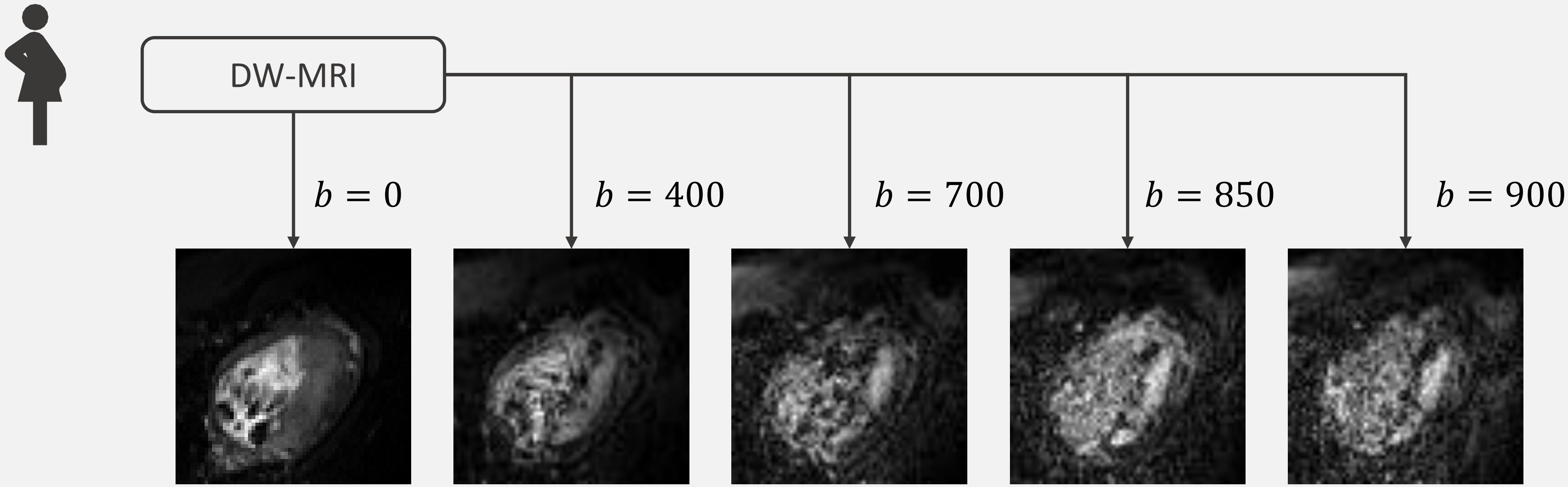
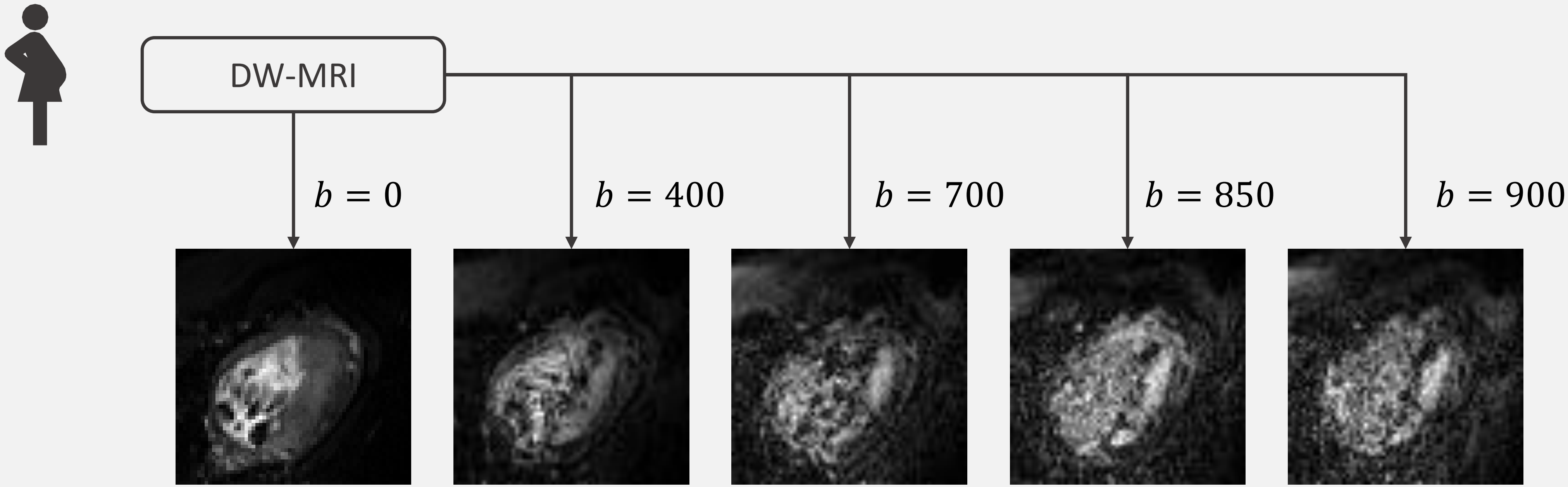
  - However, higher b-value, stronger noise
  - Ordinary registration methods fail



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

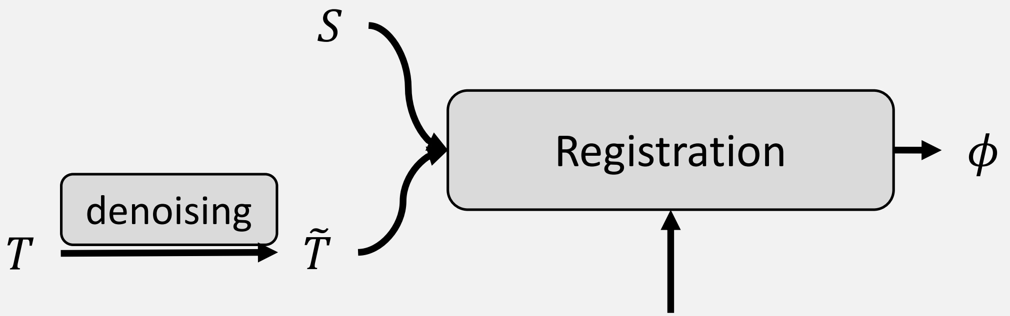
Noisy Image

Denoised image

Image: https://en.wikipedia.org/wiki/Total_variation_denoising

Related Works

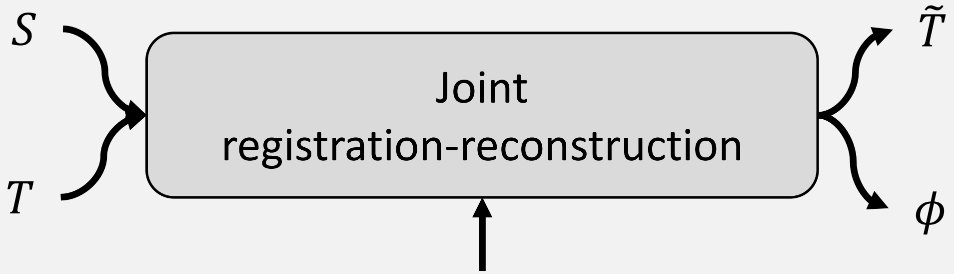
- 2-Steps Method: denoising before registration



$$\operatorname*{argmin}_{\phi} \frac{1}{\sigma^2} \mathrm{dist}\left(S \circ \phi^{-1}, \tilde{T}\right) + \mathcal{R}(\phi)$$

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

- Joint Optimization Method

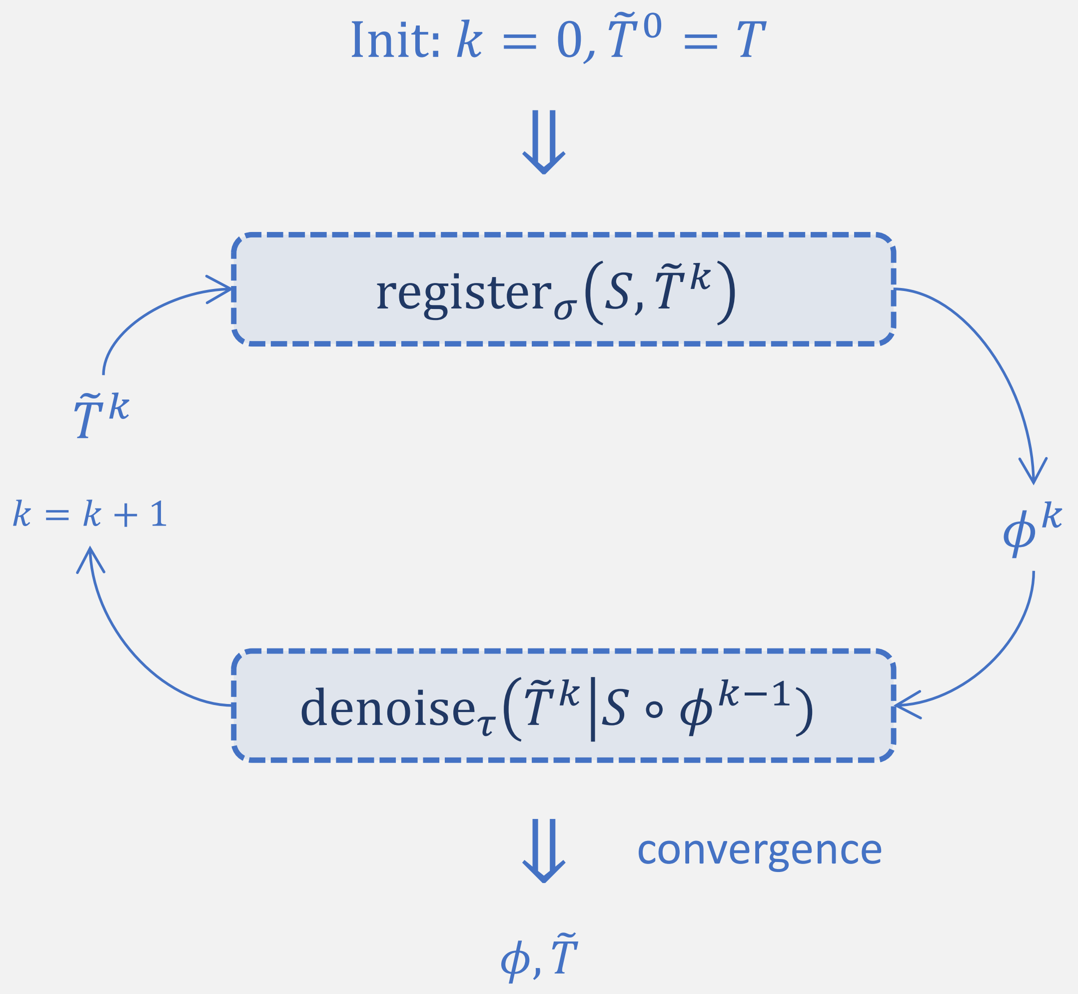


$$\operatorname*{argmin}_{\phi,T} \frac{1}{\sigma^2} \mathrm{dist}(S \circ \phi^{-1}, T) + \mathcal{R}_{\mathrm{reg}}(\phi) + \lambda_1 R_{\mathrm{denoising}}(\tilde{T}) + \lambda_2 \mathrm{dist}(T, \tilde{T})$$

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

Proposed method: PnP-RR

- Basic Idea



Proposed method: PnP-RR

- Basic Idea

Init: $k = 0, \tilde{T}^0 = T$

$\Downarrow$

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

ϕ^k

$\text{denoise}_\tau(\tilde{T}^k | S \circ \phi^{k-1})$

$k = k + 1$

$\tilde{T}^k$

$\Downarrow$ convergence

$\phi, \tilde{T}$

- Advantages

TV

TGV

BM3D

Neural Network

Flexible to CHOOSE DENOISER

Simple to IMPLEMENT

Better PERFORMANCE

WORK

WORK

Easy to TUNE

Proposed method: PnP-RR

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

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

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  - **SPLIT** Formulated as proximal algorithm

$$\underset{\tilde{T}}{\operatorname{argmin}} \frac{1}{2}\left\|\tilde{T} - Z\right\|_{L2}^2 + \tau \mathcal{R}_{\text{denoising}}(\tilde{T}) = \text{denoise}_\sigma(\tilde{T} | S \circ \phi^{-1})$$

where $Z = \dfrac{\lambda_2 T + (1/\sigma^2)(S \circ \phi^{-1})}{\lambda_2 + (1/\sigma^2)}$

$\tau = \dfrac{\lambda_1}{2\left(\lambda_2 + (1/\sigma^2)\right)}$

$$\underset{\phi}{\operatorname{argmin}} \frac{1}{\sigma^2}\left\|S \circ \phi^{-1} - \tilde{T}\right\|_{L2}^2 + \mathcal{R}_{\text{reg}}(\phi) = \text{register}_\sigma\,(S, \tilde{T}^k\,)$$

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  - **REPLACE** Formulated as PnP algorithm

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

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

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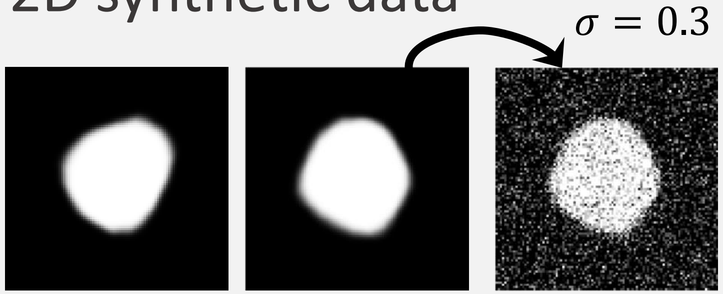
Specifying an image prior

Experiments

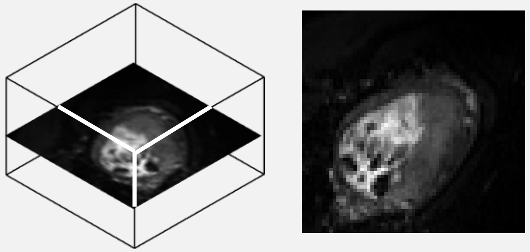
- Data
  - 2D synthetic data



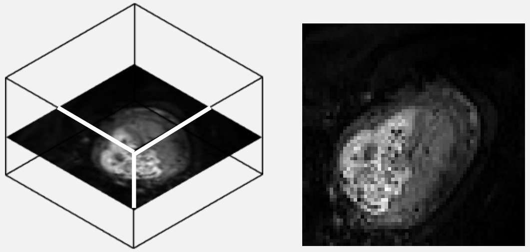
Source S Target T

  - Real 3D DW-MRI data

Source S



Target T

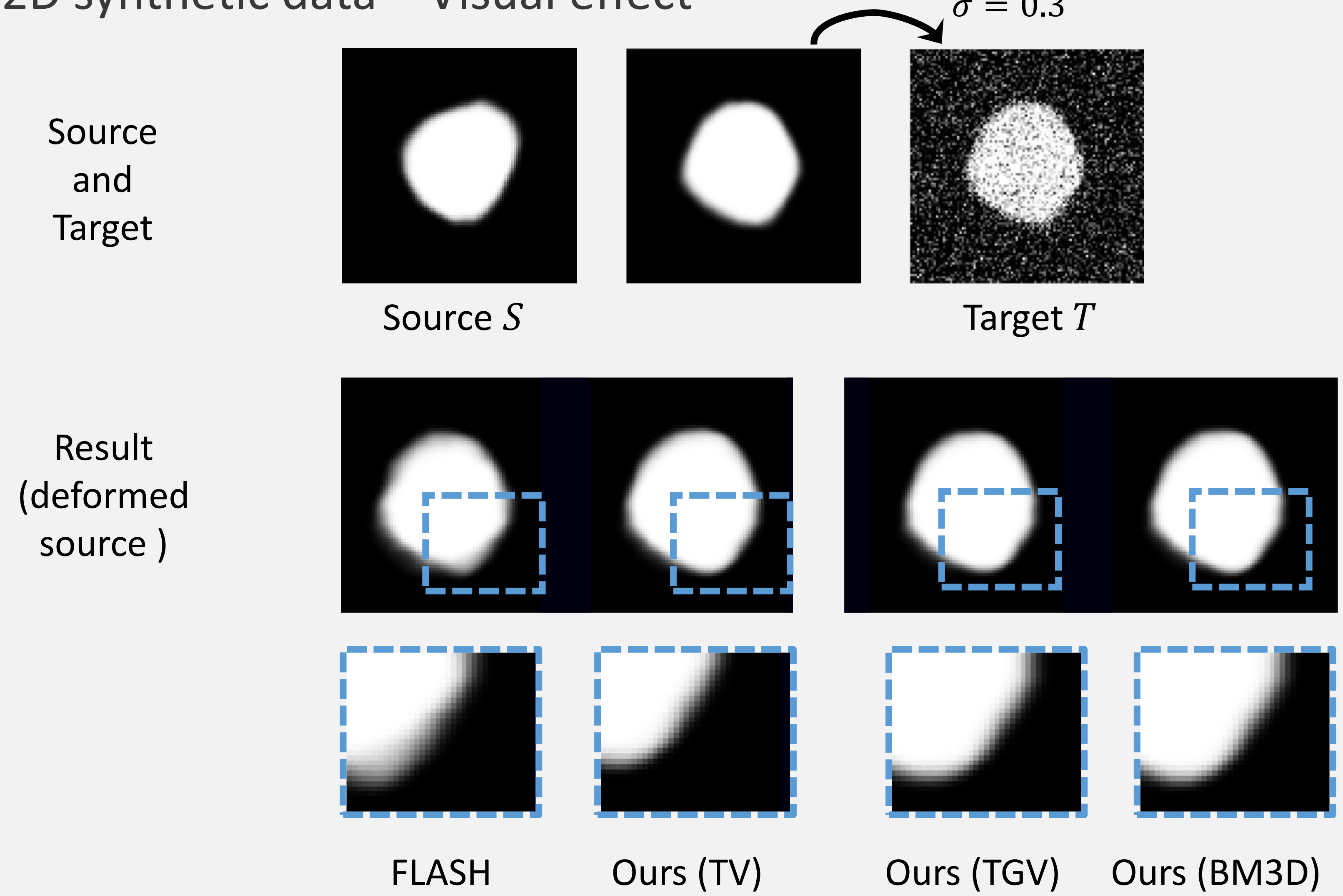


- Algorithm Setting
  - Registration algorithm
    - Fourier-approximated Lie Algebras for Shooting (FLASH)[1]
  - Denoising algorithm
    - Total variation (TV)
    - Total generalized variation (TGV)
    - Block-matching and 3D filtering (BM3D)

[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)

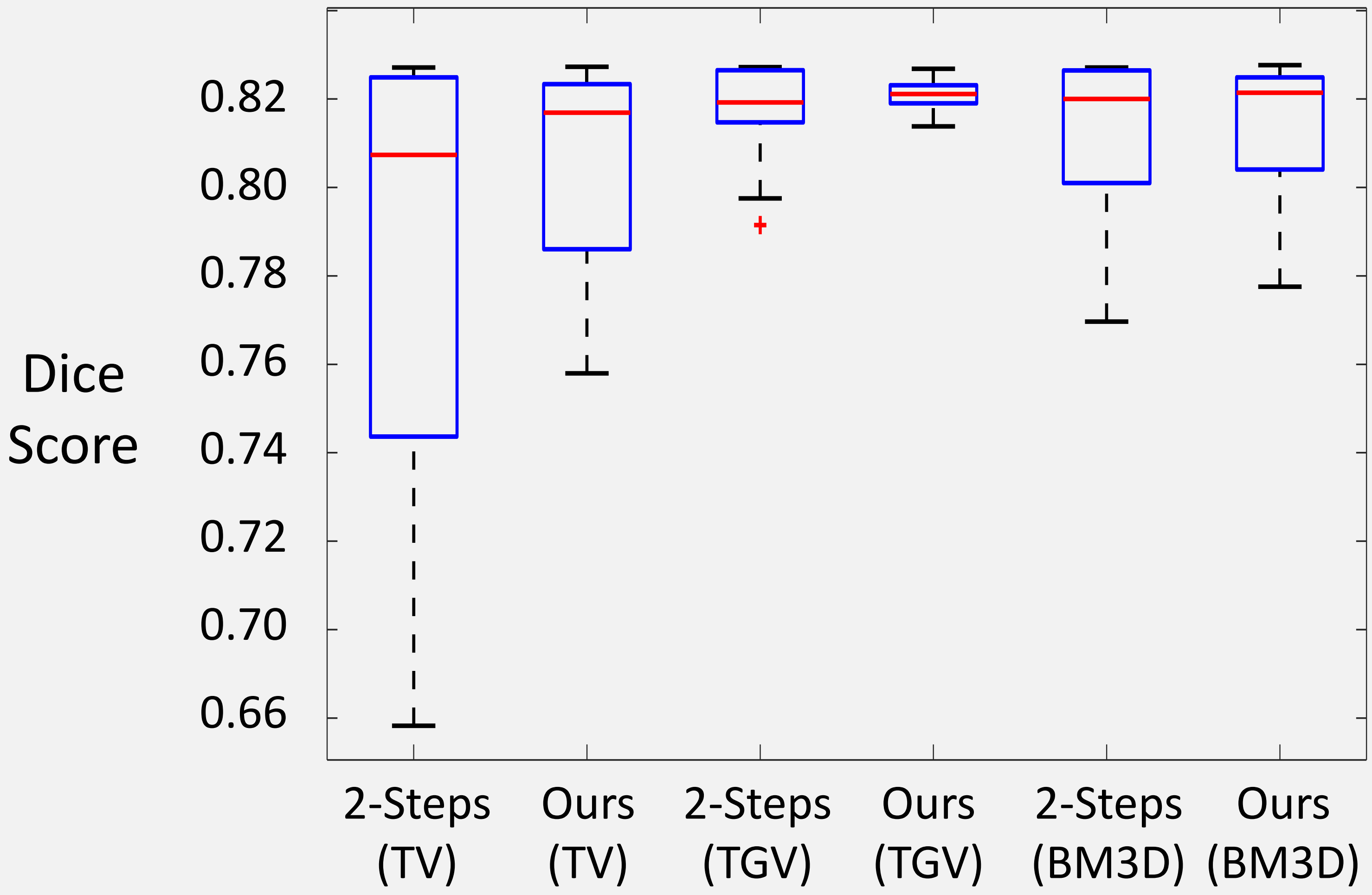
Experiments

- Result
  - 2D synthetic data – Visual effect



Experiments

- Result
  - 2D synthetic data – Quantitative performance



Experiments

- Data
  - Real 3D DW-MRI data

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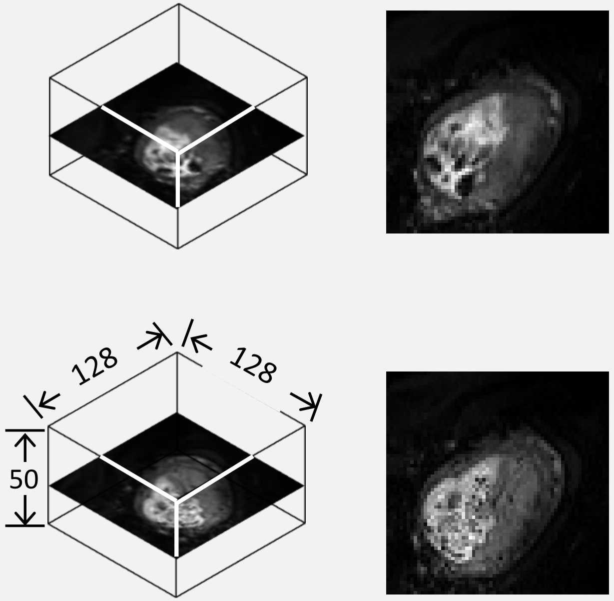
Target T



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

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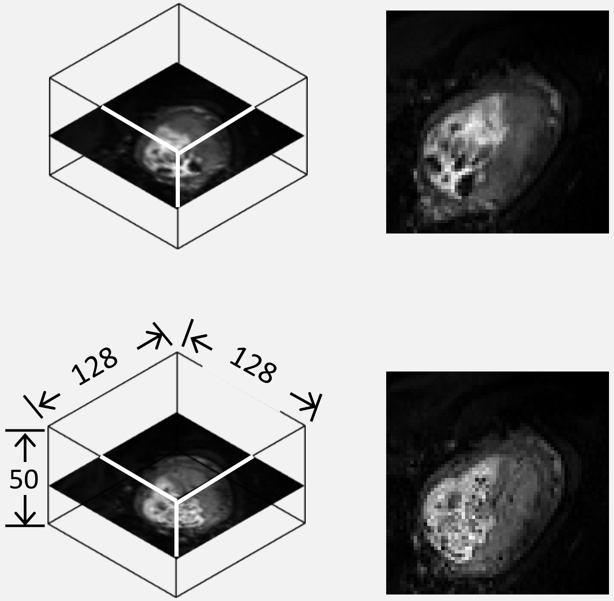

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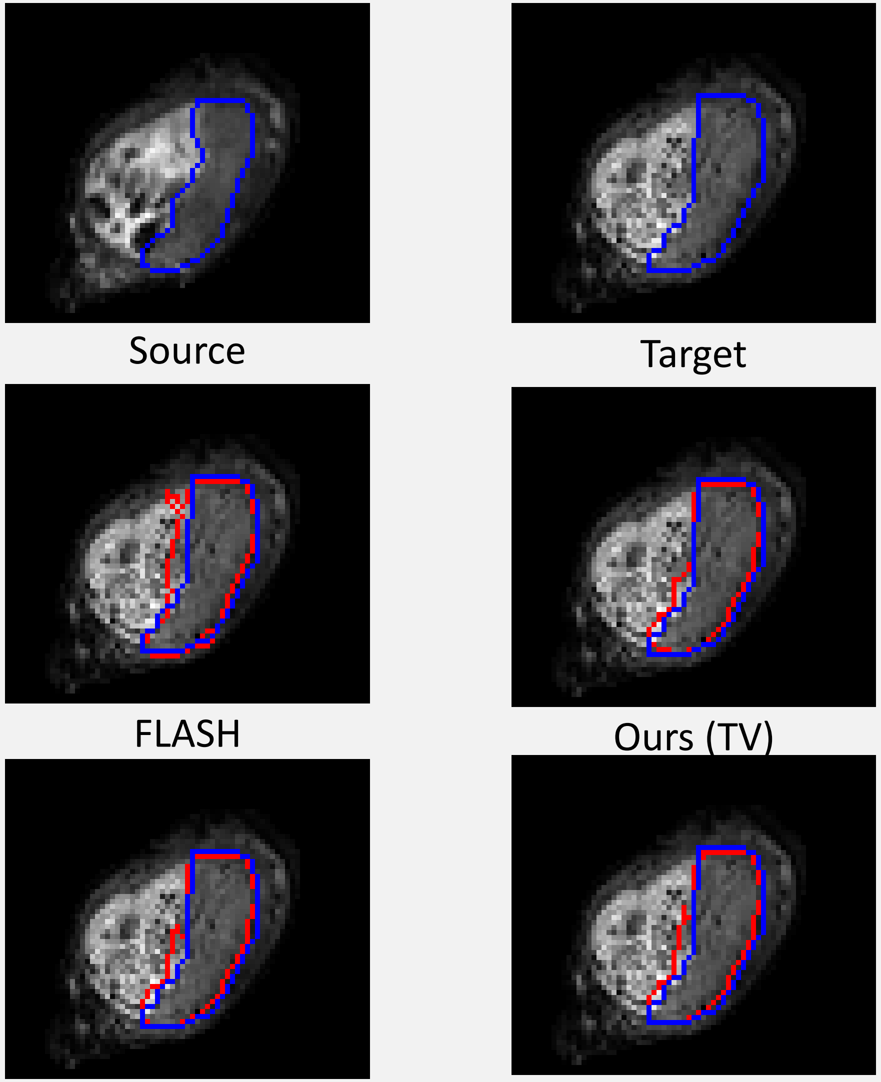

Source, Target, FLASH, Ours (TV), Ours (TGV), Ours (BM3D)

Discussion

- Performance
  - Data
  - Advanced methods
- Convergence
- Time

Conclusion

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

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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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