Paper

Slides

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

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[6] Computer Science, University of Virginia, Charlottesville, USA

Paper

Slides

Brief Intro

- We proposed **plug-and-play reconstruction-registration method (PnP-RR):**

  1) Is a deformable image **registration** framework for **severely noise-corrupted images**
  2) Is used for registering placental diffusion-weighted MR images that contains severely noise

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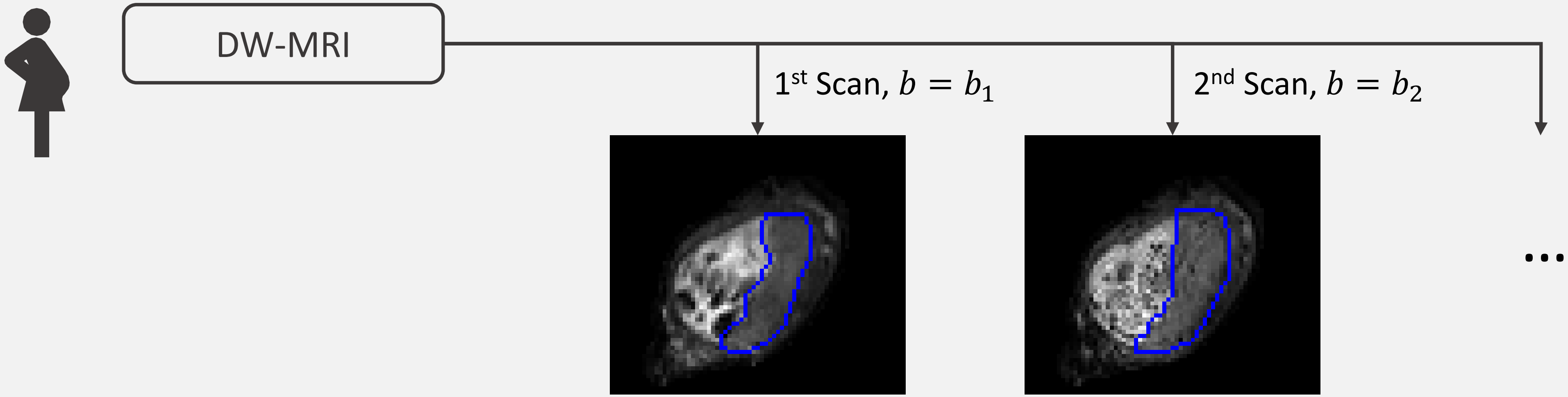
Contents

1. Background
   1) DW-MRI
   2) Image registration
2. Related works
3. Proposed method: PnP-RR
4. Experiments and results
5. Discussion and conclusion

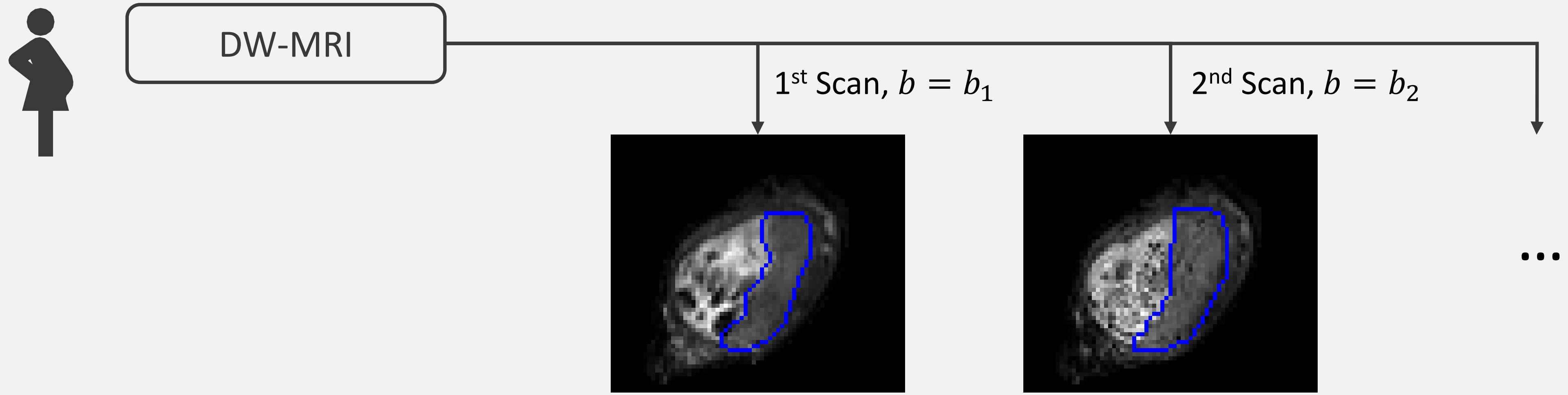
Background

- Placenta and DW-MRI
  - **Diffusion-weighted MRI (DW-MRI)** for placental health monitoring



Background

- Placenta and DW-MRI
  - Diffusion-weighted MRI (DW-MRI) for placental health monitor
  - Collect **several placental DW-MR images** with **different parameters (b-values),** then **track** the appearance changes



Background

- Placenta and DW-MRI
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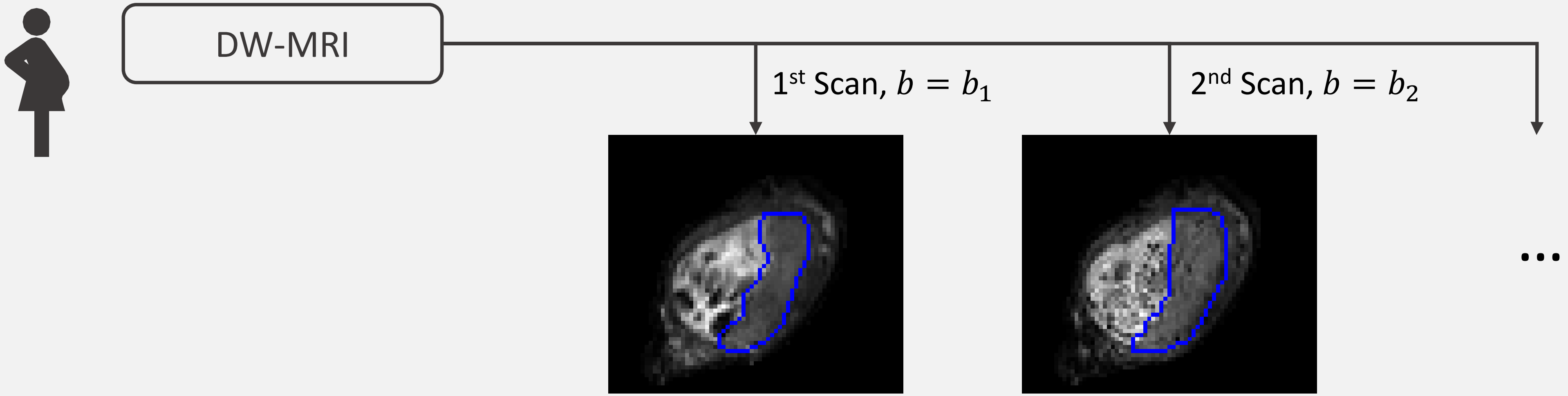
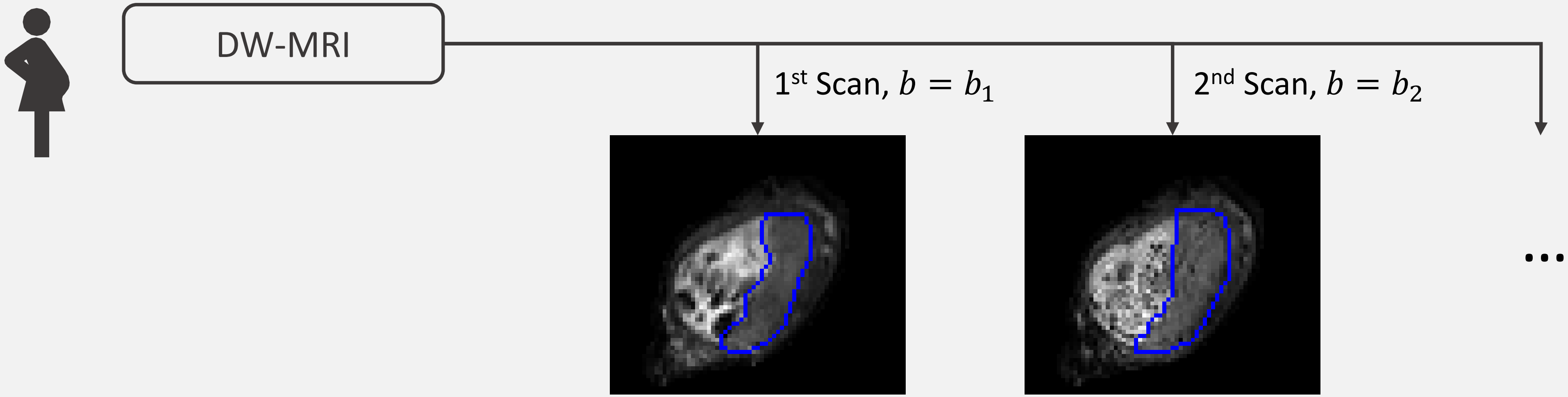
  - Collect several placental DW-MR images with different parameters (b-values); then track the appearance changes
  - **Deformation** among images due to maternal breathing and fetal movements **makes tracking hard**



Background

- Placenta and DW-MRI
  - Diffusion-weighted MRI (DW-MRI) for placental health monitor
  - Collect several placental DW-MR images with different parameters (b-values); then track the appearance changes
  - Deformation among images due to maternal breathing and fetal movements makes tracking hard
  - Need **Image registration** to **find and cancel the deformation**



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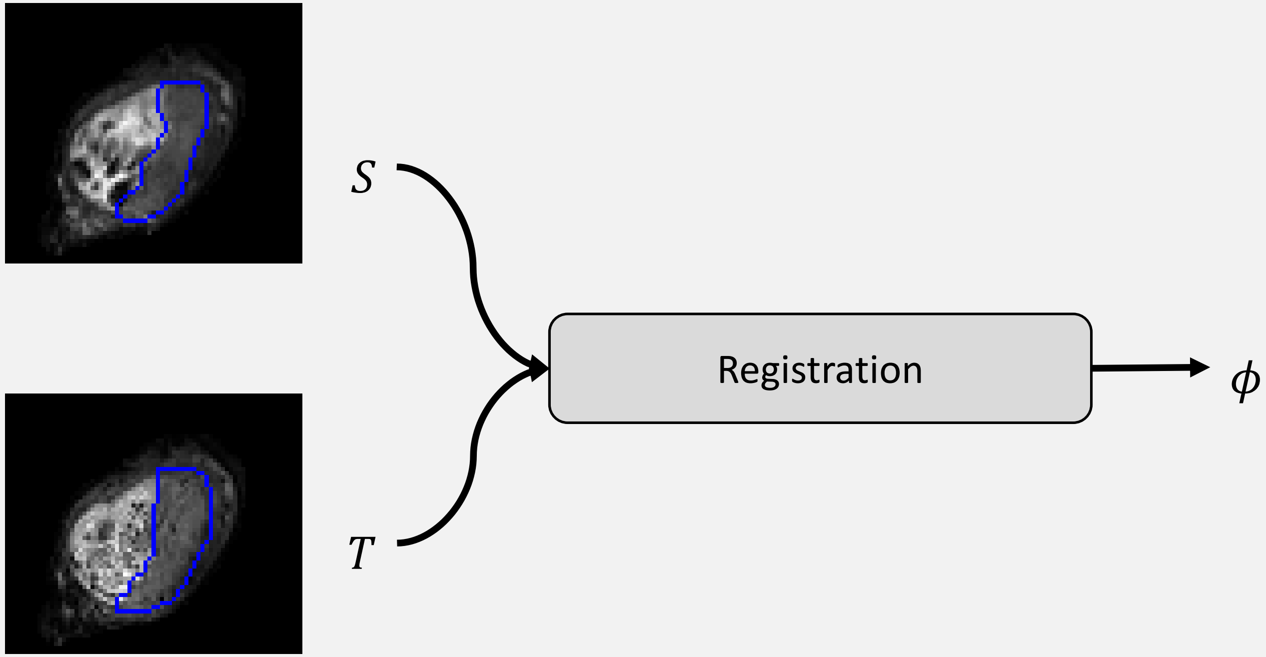
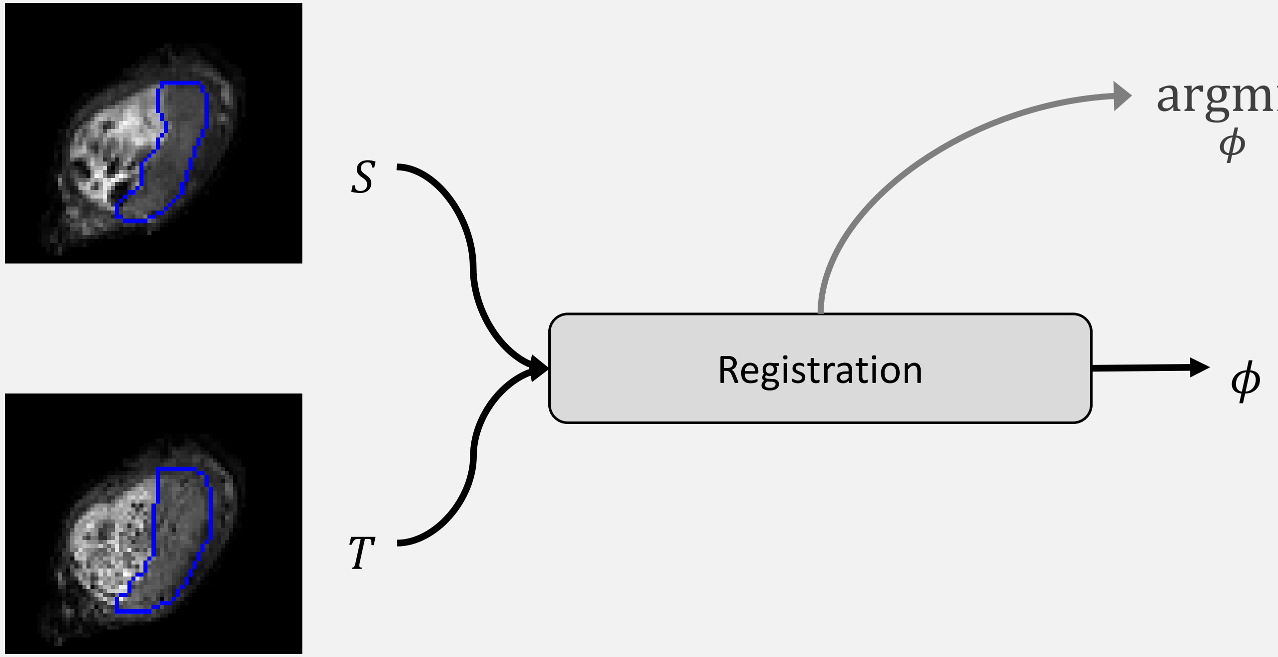
- Image Registration
  - **Task: find the deformation** ϕ between a source Image S and a target image T



Background

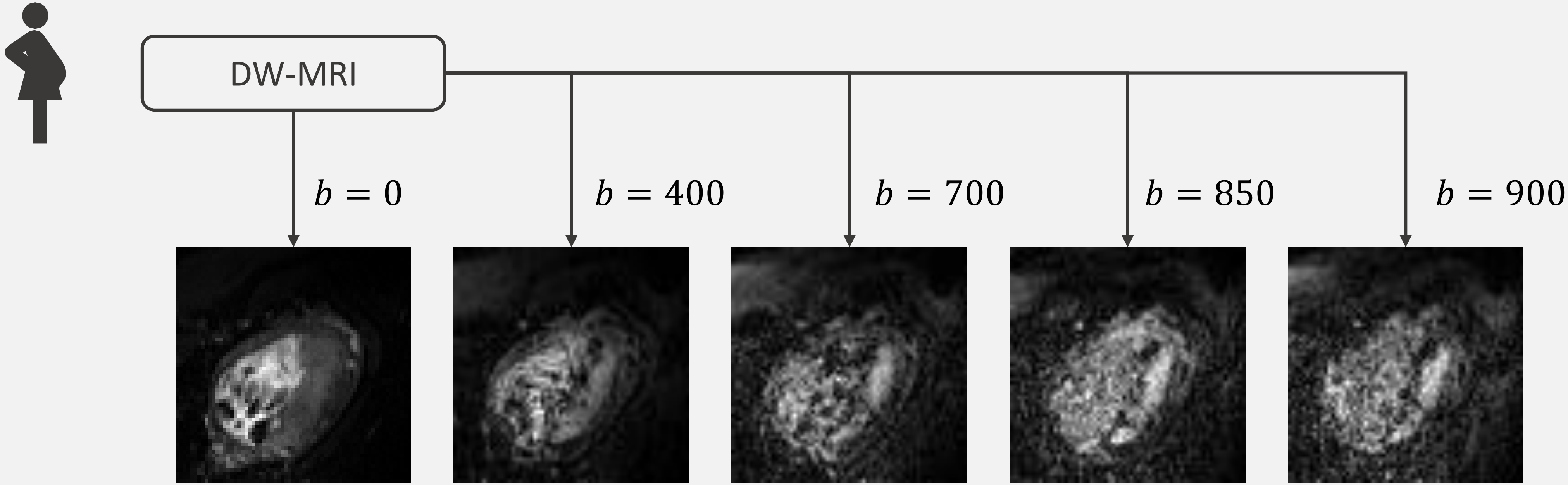
- Image Registration
  - Task: find the deformation ϕ between a source Image S and a target image T
  - Current mainstream: **optimization-based methods**



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

Background

- B-value and noise
  - Higher **b-value**, stronger **noise**



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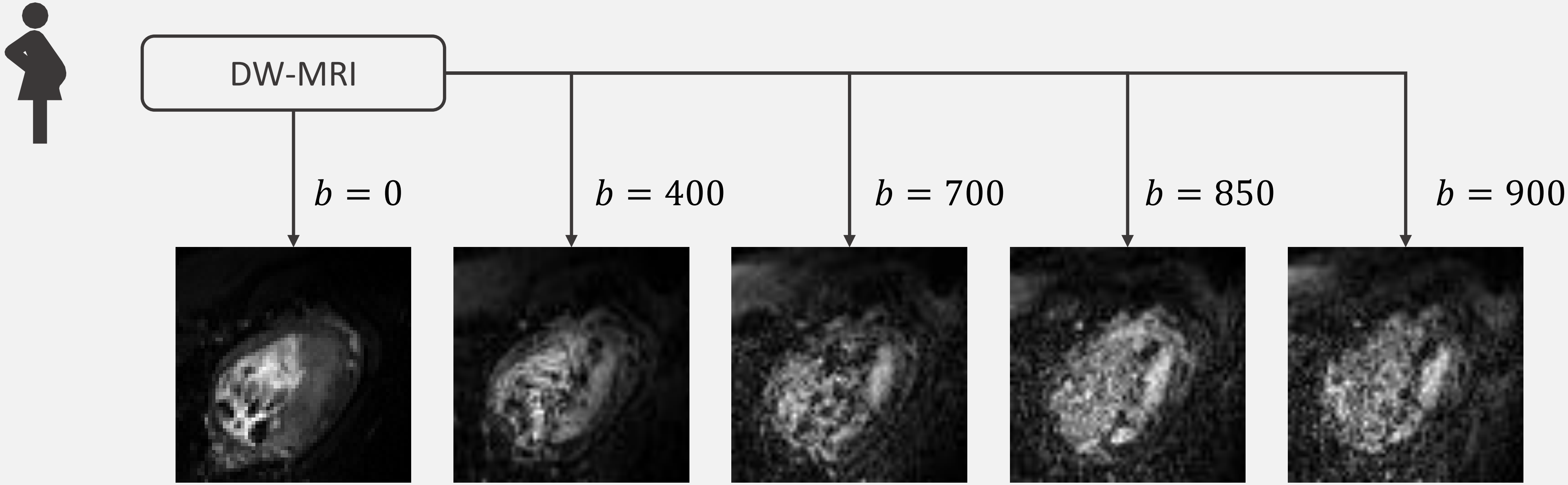
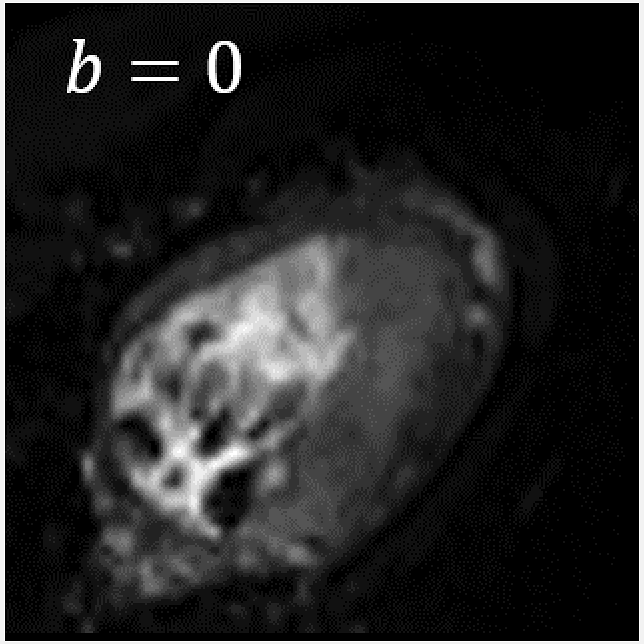
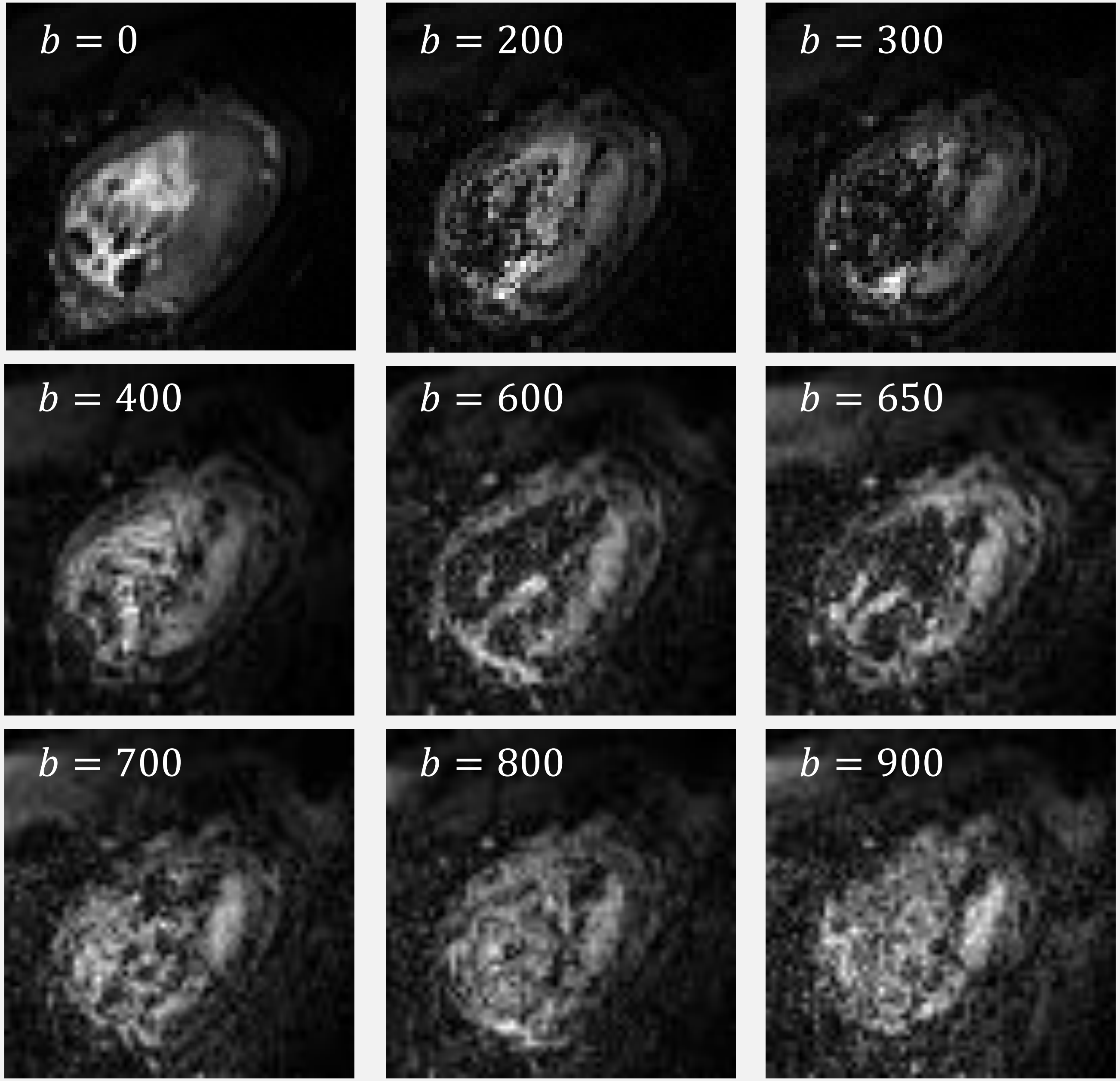
  - Ordinary registration methods: fail on severely noise-corrupted images



Background

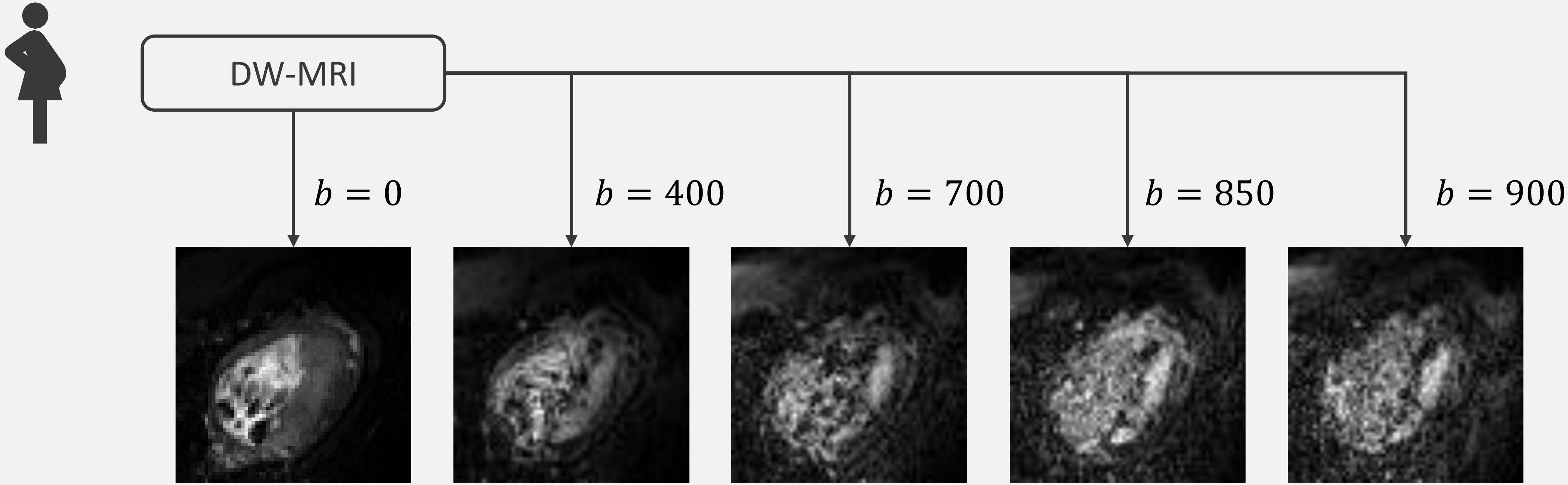
- B-value and noise
  - DW-MRI images with different b-values





Background

- B-value and noise
  - Higher b-value, stronger noise
  - Ordinary registration methods: fail on severely noise-corrupted images
  - A noise-robust image registration methods is needed



Related Works

- Basic idea: denoising + registration
  - **Integrate** image registration with **denoising**

Related Works

- Basic idea: denoising + registration
  - **Integrate** image registration with **denoising**
  - Denoising **example**: total variation denoising for white Gaussian noise

Original

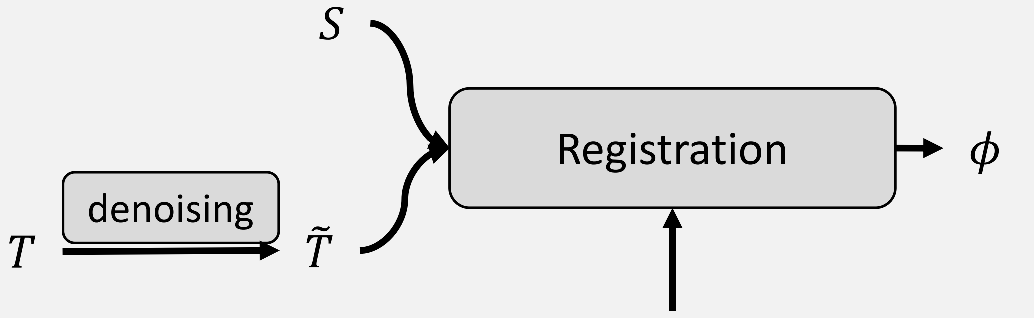
Noisy Image

Denoised image

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

Related Works

- 2-Steps Method: denoising before registration

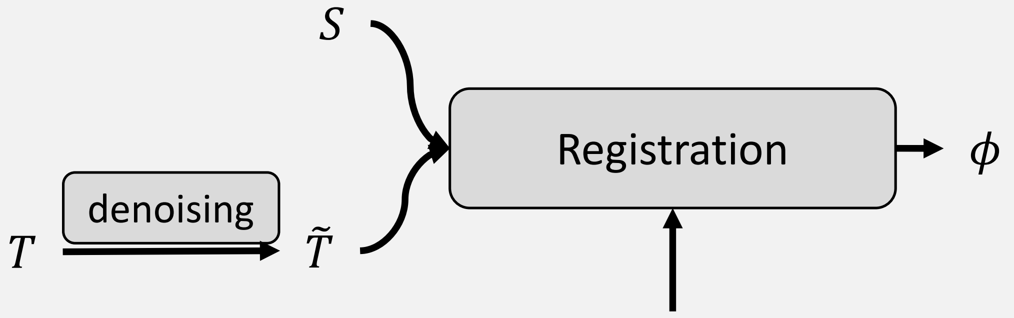


$$\underset{\phi}{\operatorname{argmin}} \frac{1}{\sigma^2} \operatorname{dist}\left(S \circ \phi^{-1}, \tilde{T}\right) + \mathcal{R}(\phi)$$

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

Related Works

- 2-Steps Method: denoising before registration



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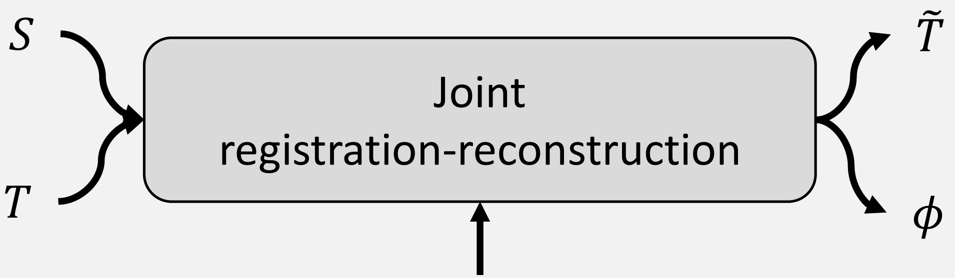
- Joint Optimization Method



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

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

Proposed method: PnP-RR

- Basic Idea

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

$\Downarrow$

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

ϕ^k

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

$k = k + 1$

$\tilde{T}^k$

$\Downarrow$ convergence

$\phi, \tilde{T}$

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- Basic Idea

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$\text{register}_\sigma(S, \tilde{T}^k)$ $\rightarrow$ ϕ^k $\rightarrow$ $\text{denoise}_\tau(\tilde{T}^k | S \circ \phi^{k-1})$ $\rightarrow$ $k = k + 1$ $\rightarrow$ $\tilde{T}^k$ $\rightarrow$ $\text{register}_\sigma(S, \tilde{T}^k)$

$\Downarrow$ convergence

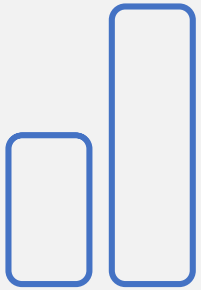
$\phi, \tilde{T}$

- Advantages

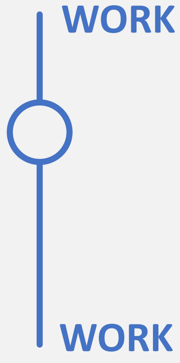
- TV ✔
- TGV ✔
- BM3D ✔
- Neural Network ✔

Flexible to CHOOSE DENOISER

Simple to IMPLEMENT



Better PERFORMANCE



Easy to TUNE

Proposed method: PnP-RR

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

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

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  - **SPLIT** Formulated as proximal algorithm

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

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

where

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

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

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Replace with arbitrary denoiser

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

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

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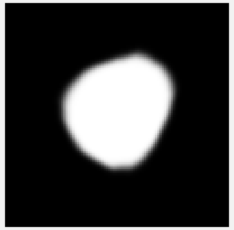
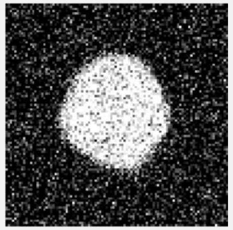
Specifying an image prior

Experiments

- Data
  - 2D synthetic data



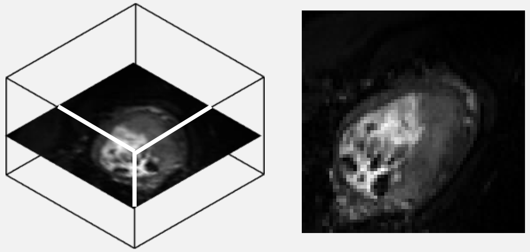
Source S



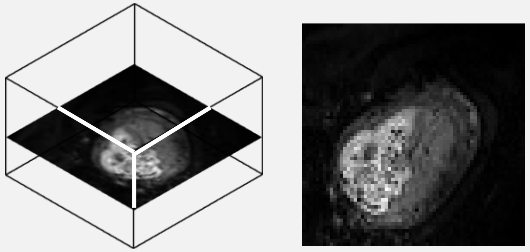
Target T

  - 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)

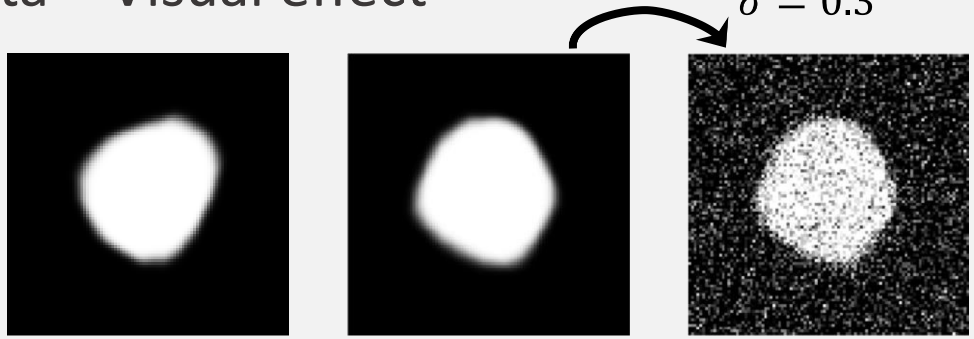
[1] Zhang, M., Liao, R., Dalca, A.V., Turk, E.A., Luo, J., Grant, P.E., Golland, P.: Frequency diffeomorphisms for efficient image registration. In: International conference on information processing in medical imaging. pp. 559–570. Springer (2017)

Experiments

- Result
  - 2D synthetic data – Visual effect

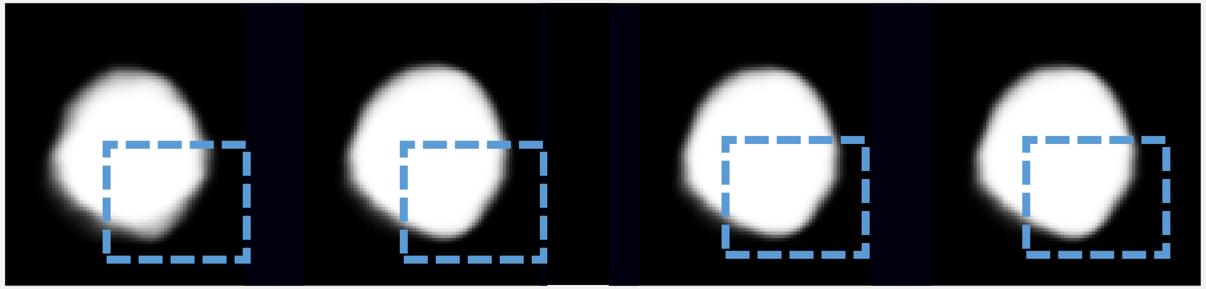
$\sigma = 0.3$

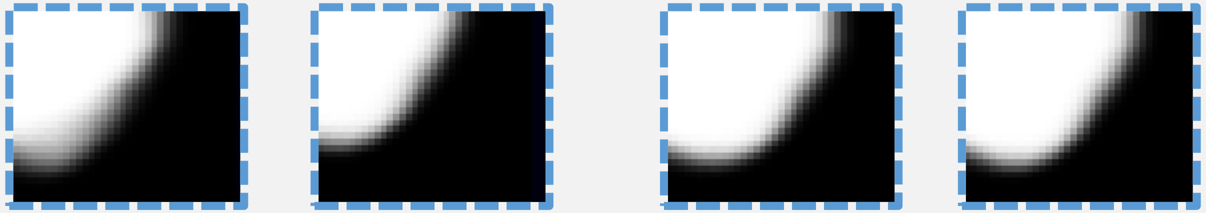
Source and Target



Source S Target T

Result (deformed source)

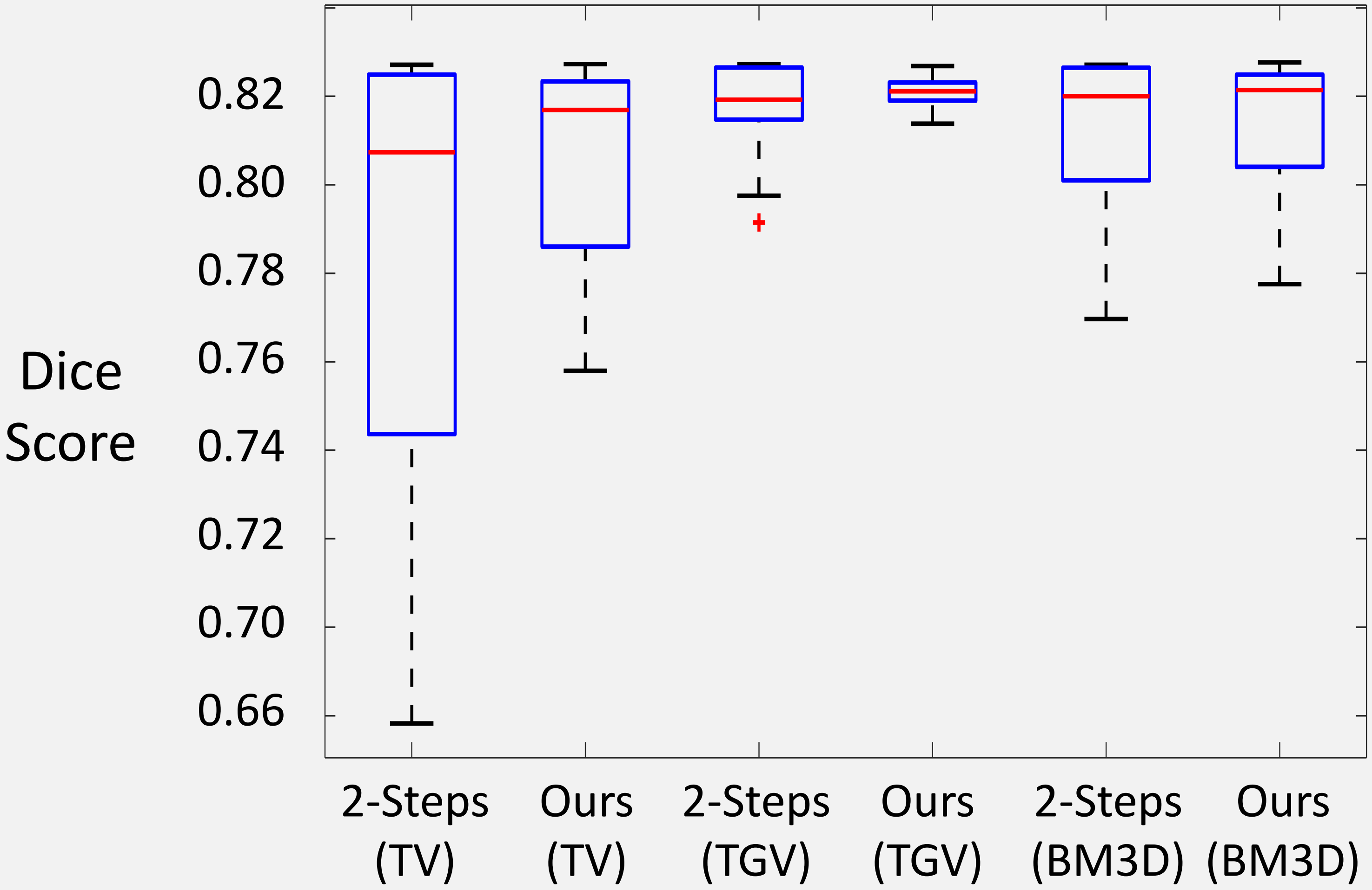




FLASH Ours (TV) Ours (TGV) Ours (BM3D)

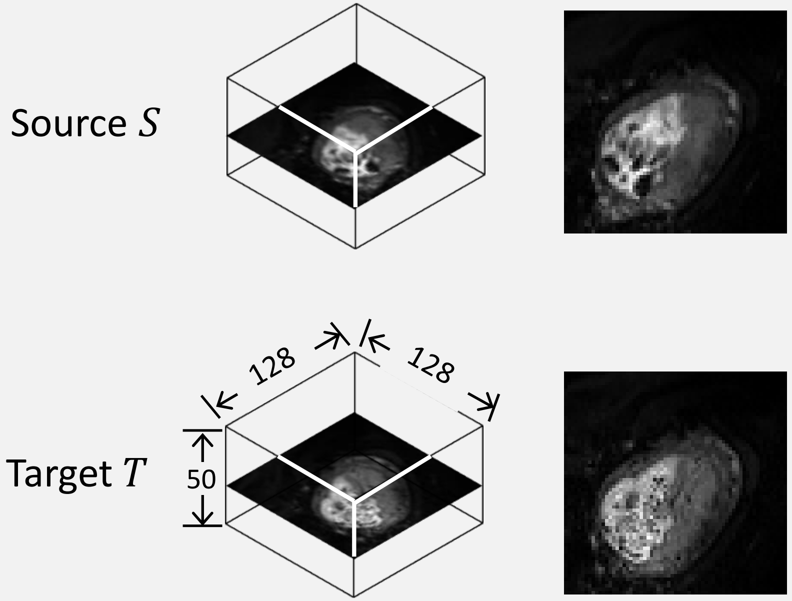
Experiments

- Result
  - 2D synthetic data – Quantitative performance



Experiments

- Data
  - Real 3D DW-MRI data



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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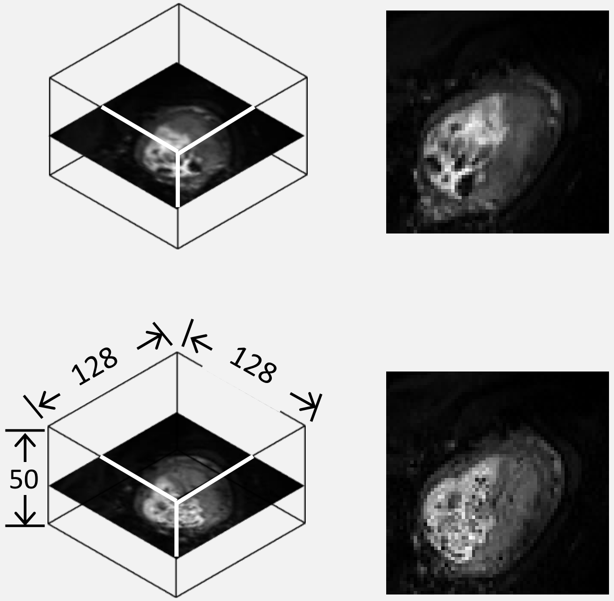

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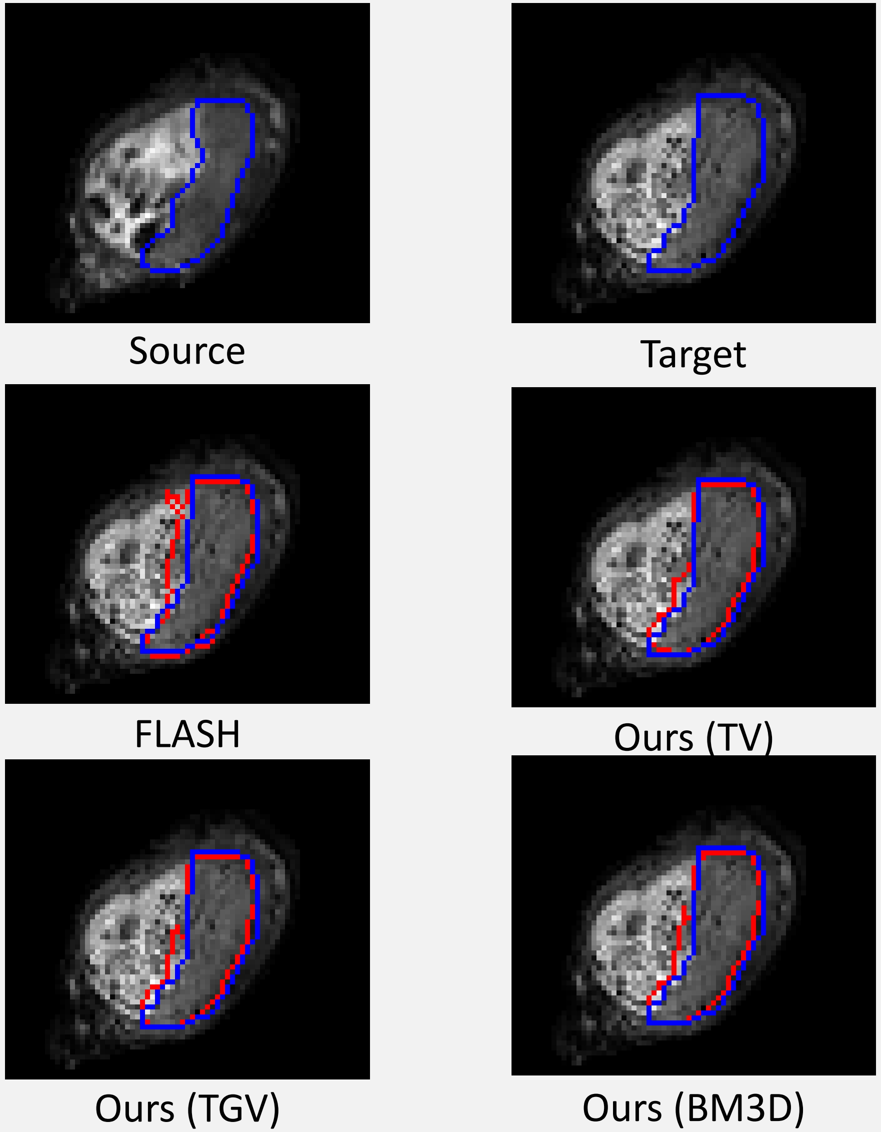

Discussion

- 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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- Questions?

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