Paper

Slides

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

Jiarui Xing[1], Ulugbek Kamilov[2,3], Wenjie Wu[4,5], Yong Wang[5], and Miaomiao Zhang[1,6]

[1] Electrical and Computer Engineering, University of Virginia, Charlottesville, USA
[2] Computer Science and Engineering, Washington University in St. Louis, USA
[3] Electrical and Systems Engineering, Washington University in St. Louis, USA
[4] Biomedical Engineering, Washington University in St. Louis, USA.
[5] Obstetrics and Gynecology, Washington University in St. Louis, USA.
[6] Computer Science, University of Virginia, Charlottesville, USA

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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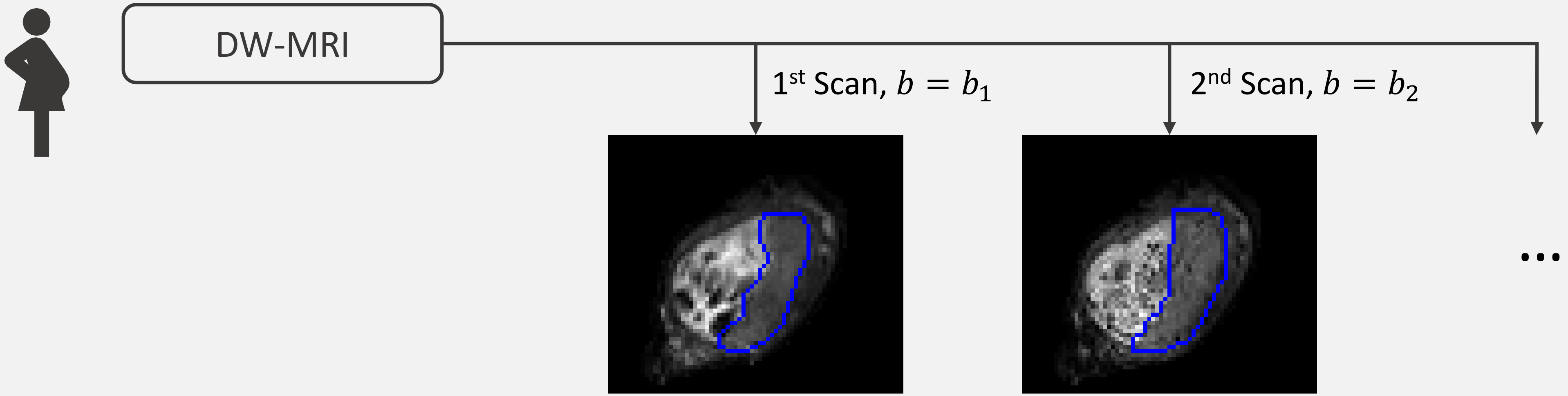
Contents

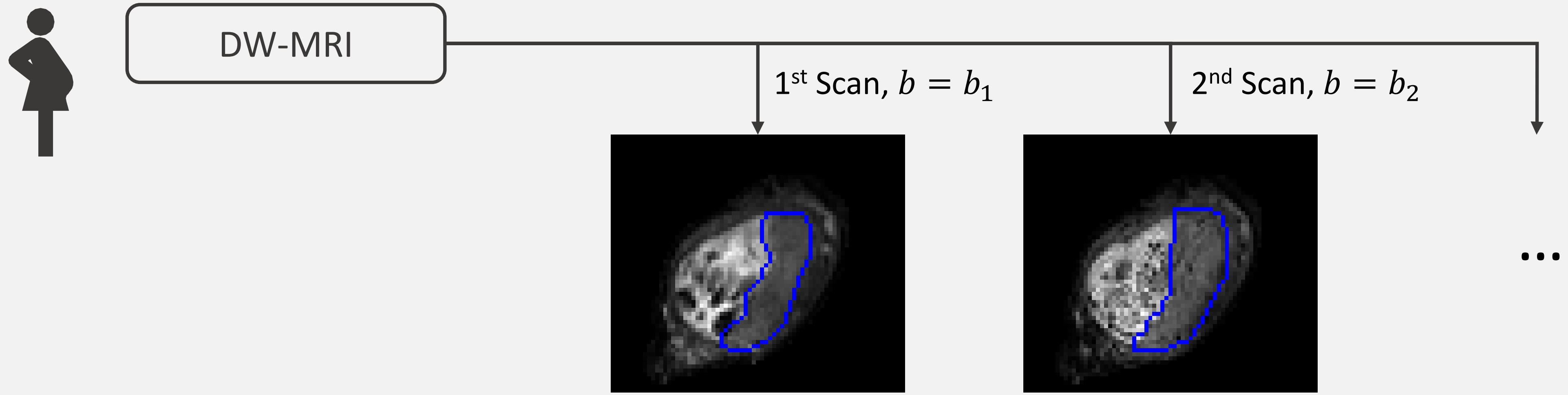
Background

- 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



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- Placenta and DW-MRI
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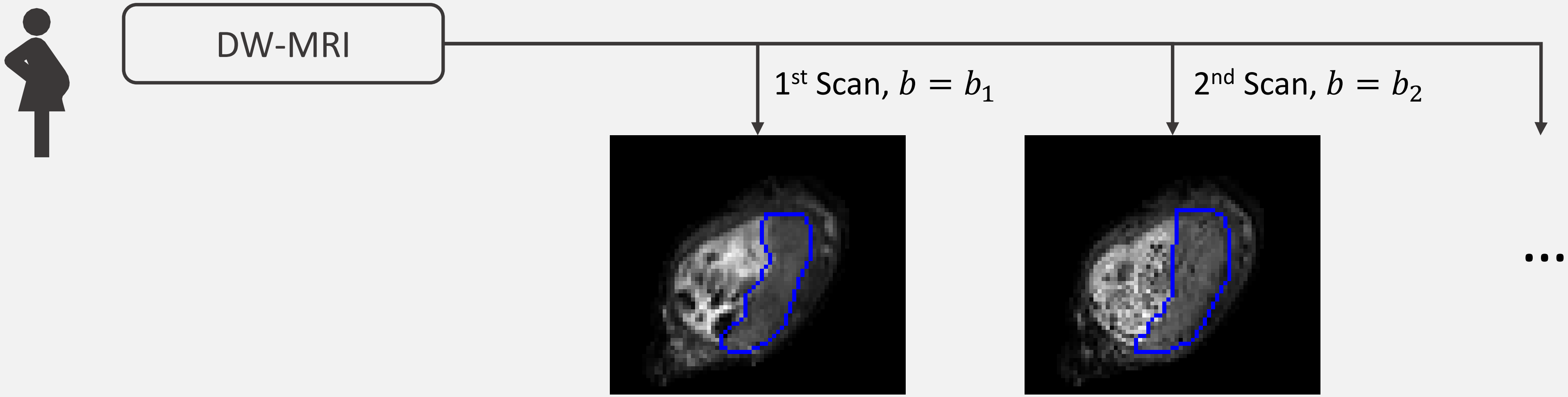
  - **Deformation** among images due to maternal breathing and fetal movements **makes tracking hard**



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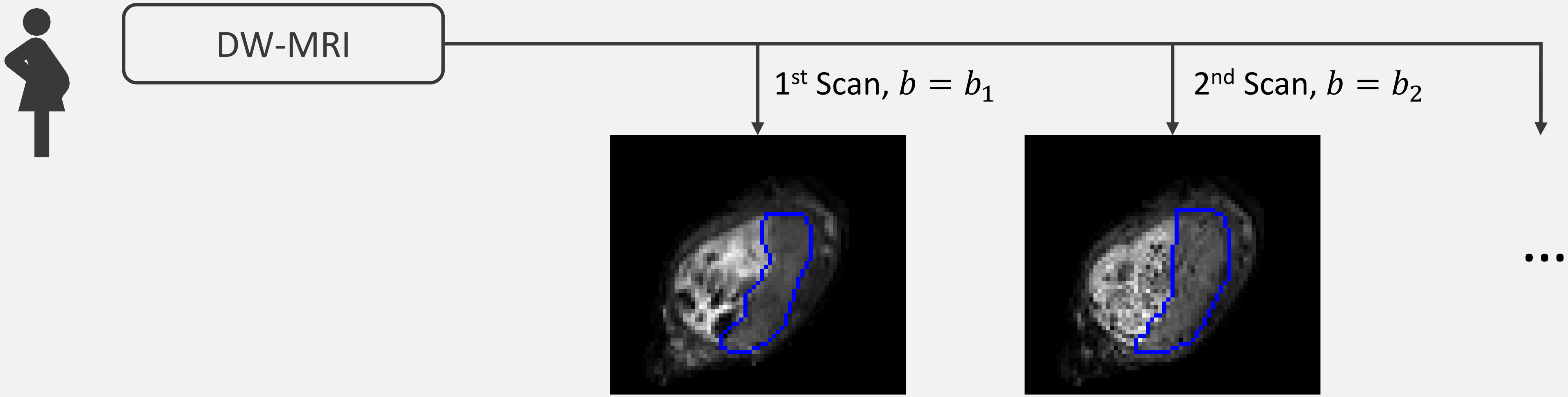
  - Diffusion-weighted MRI (DW-MRI) for placental health monitor
  - Collect several placental DW-MR images with different parameters (b-values); then track the appearance changes
  - Deformation among images due to maternal breathing and fetal movements makes tracking hard
  - Need **Image registration**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



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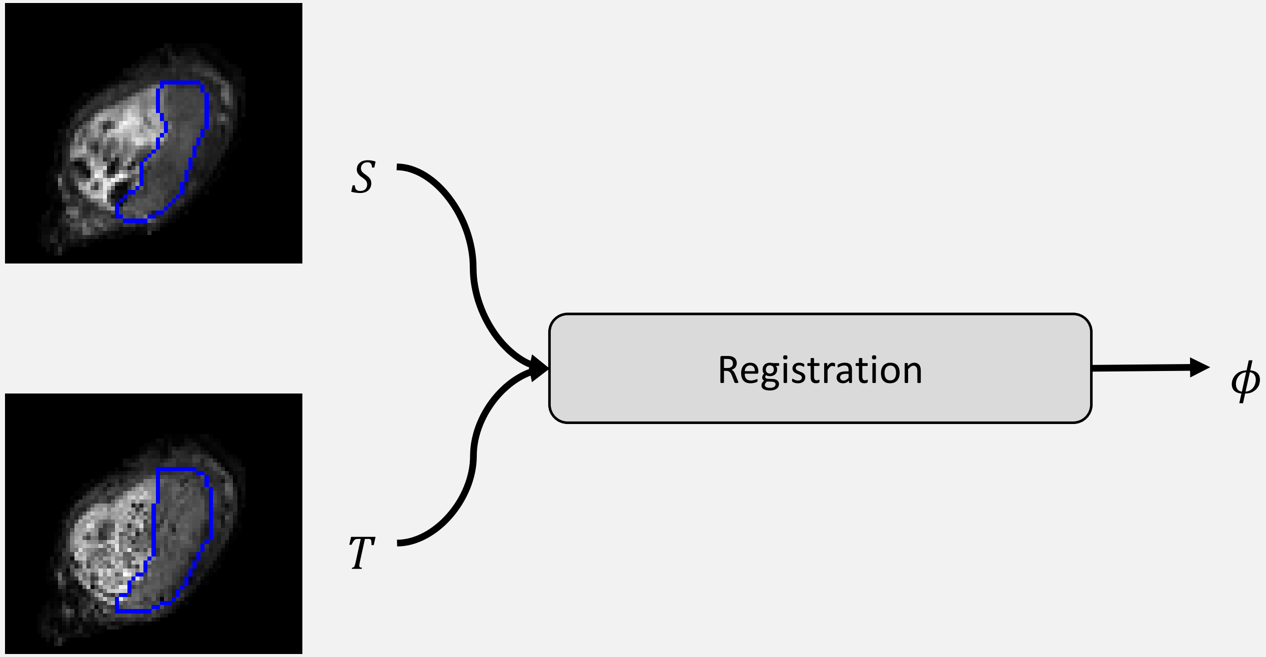
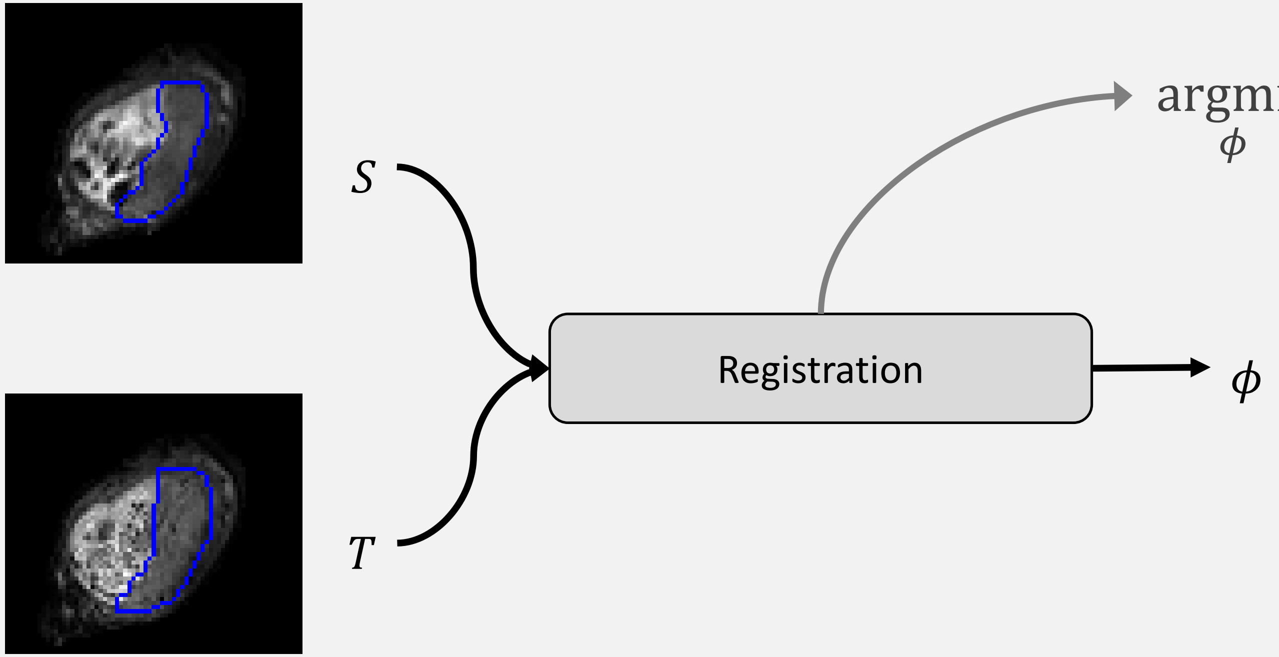
- Image Registration
  - **Task: find the deformation** ϕ between a source Image S and a target image T



Background

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

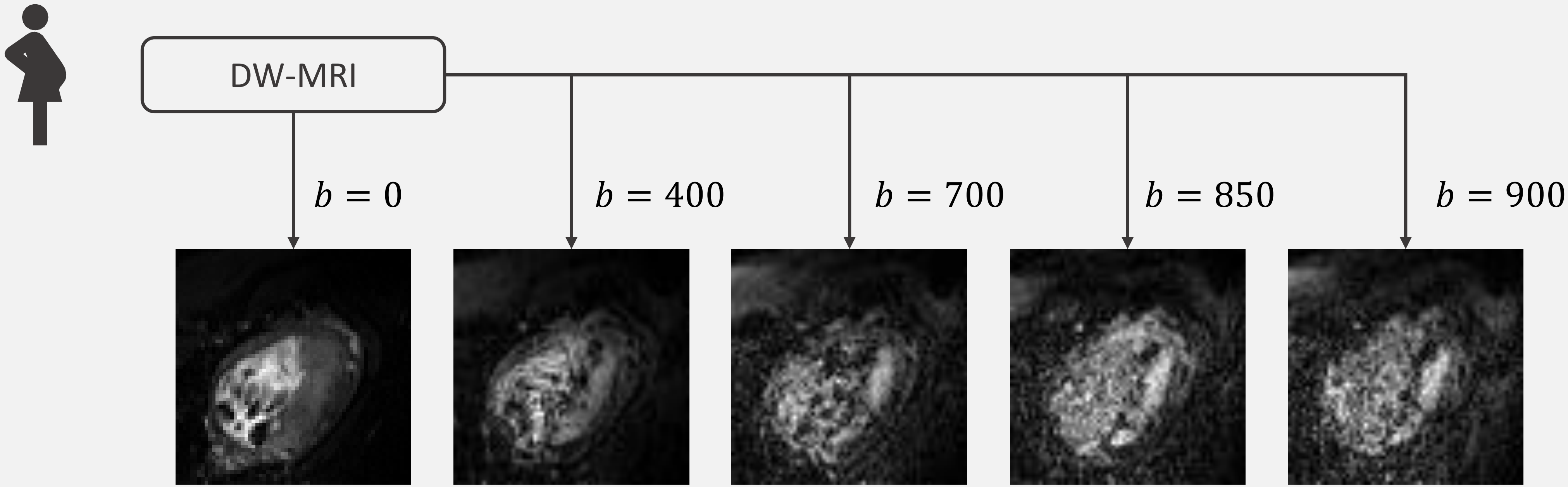


$$\underset{\phi}{\operatorname{argmin}} \boxed{\frac{1}{\sigma^2}} \boxed{\operatorname{dist}(S \circ \phi^{-1}, T)} + \boxed{\mathcal{R}(\phi)}$$

Noise variance | Image dissimilarity | Regularization for smooth transformation

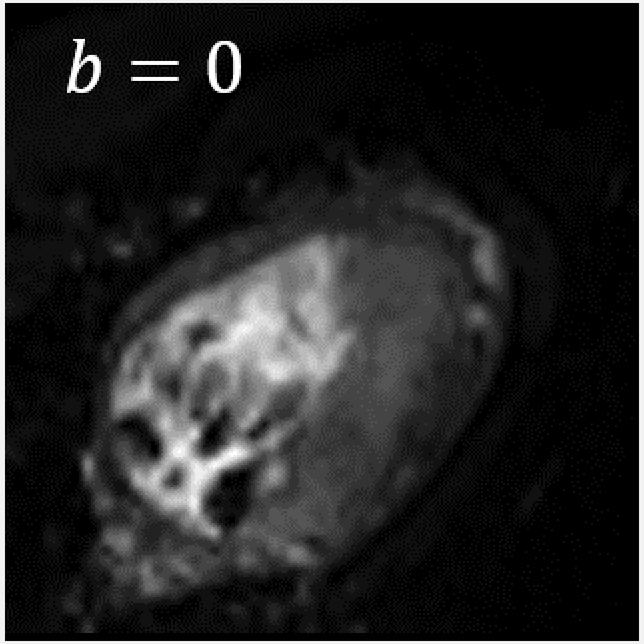
Background

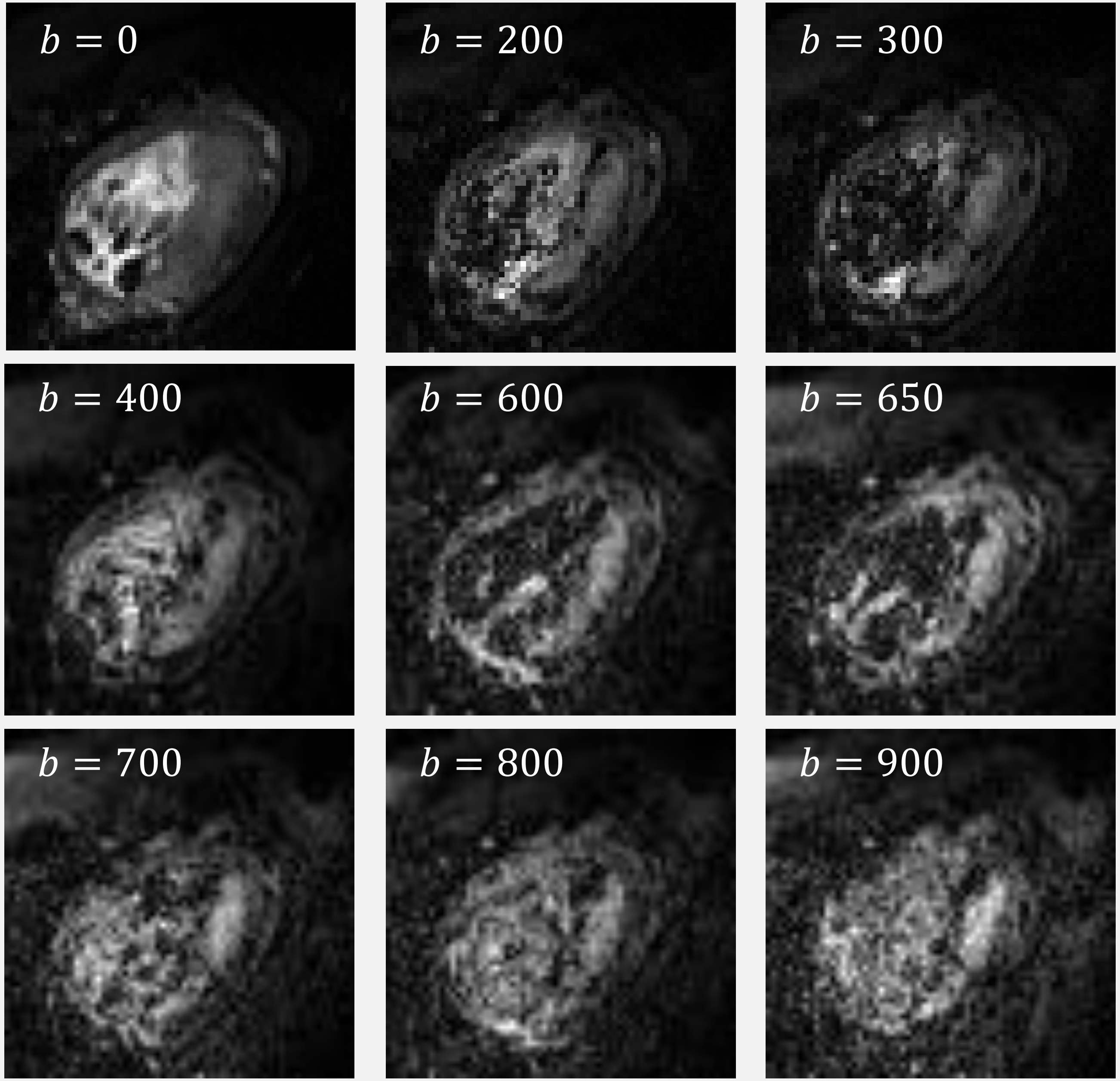
- B-value and noise
  - Higher **b-value**, stronger **noise**



Background

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





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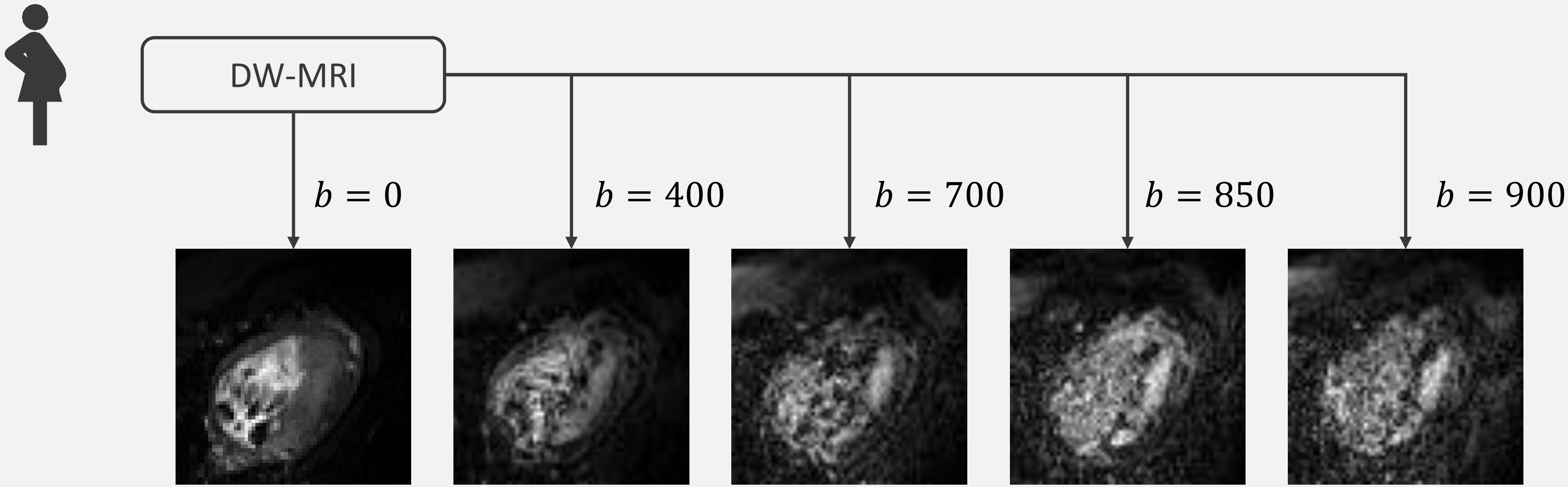
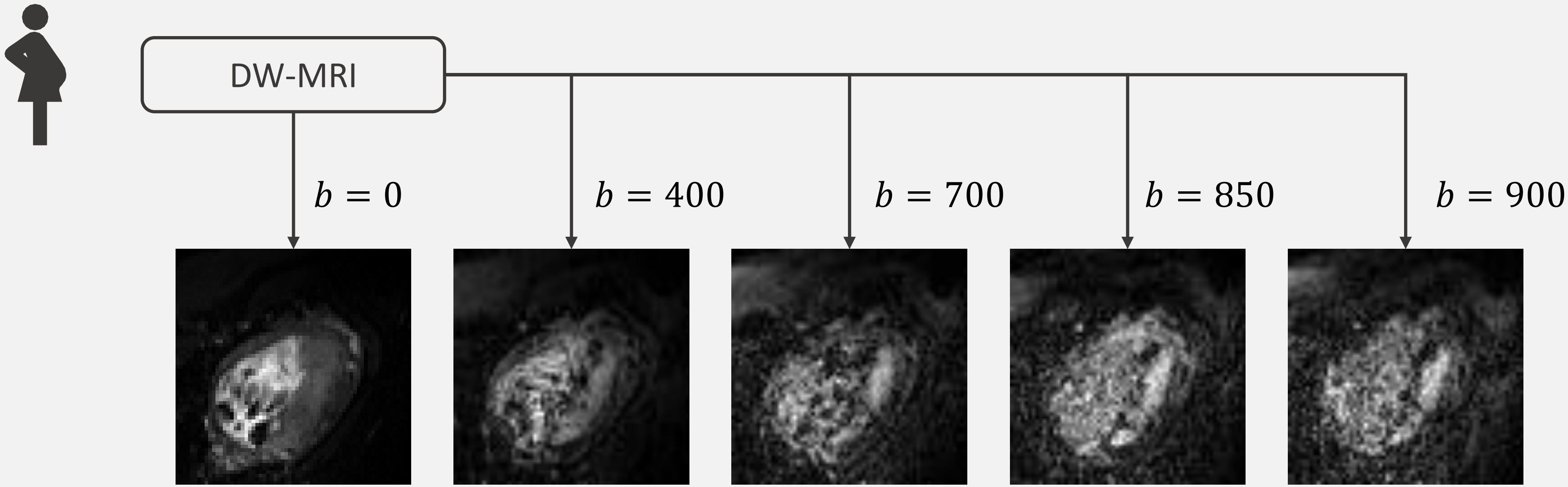
  - Ordinary registration methods: fail on severely noise-corrupted images



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
  - Find a method to **integrate** image registration with **denoising**

Related Works

- Basic idea: denoising + registration
  - Find a method to integrate image registration with denoising
  - Denoising **example**: TV denoising for white Gaussian noise

Original

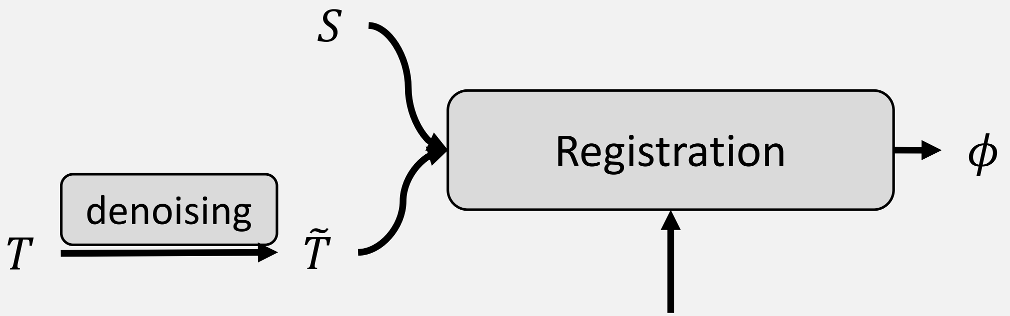
Noisy Image

Denoised image

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

Related Works

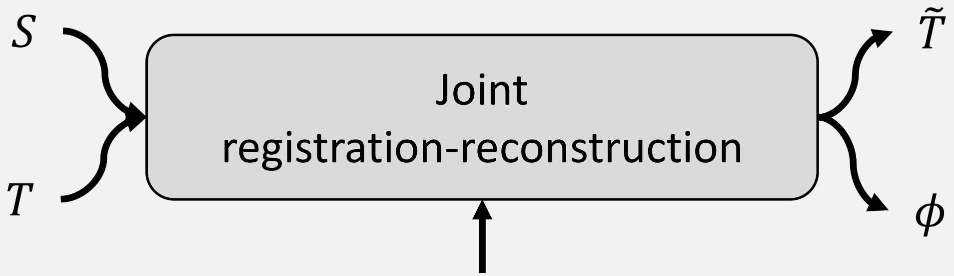
- 2-Steps Method: denoising before registration



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

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

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

$\Downarrow$

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

$\tilde{T}^k$

$k = k + 1$

ϕ^k

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

$\Downarrow$ convergence

$\phi, \tilde{T}$

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- Advantages

TV ✓

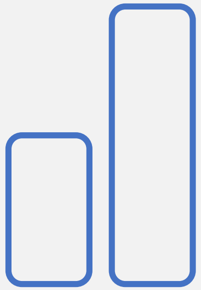
TGV ✓

BM3D ✓

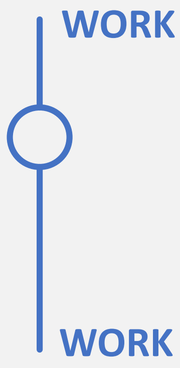
Neural Network ✓

Flexible to CHOOSE DENOISER

Simple to IMPLEMENT



Better PERFORMANCE



Easy to TUNE

Proposed method: PnP-RR

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

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

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  - **SPLIT** Formulated as proximal algorithm

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

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

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

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

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

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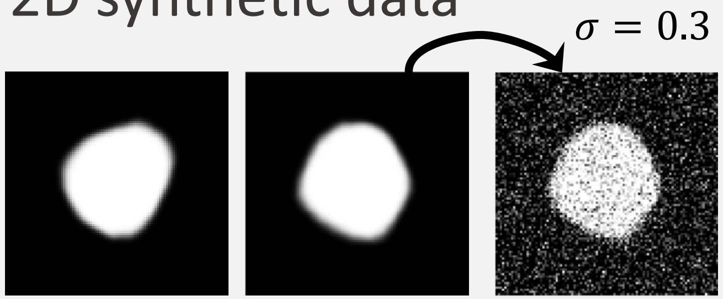
Specifying an image prior

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

Experiments

- Data
  - 2D synthetic data

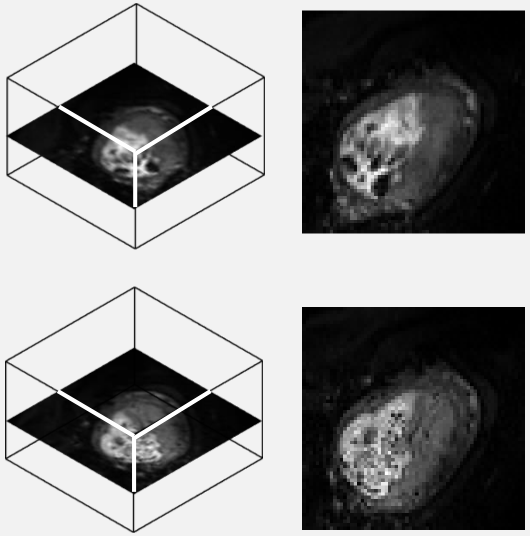


Source S Target T

  - Real 3D DW-MRI data

Source S

Target T

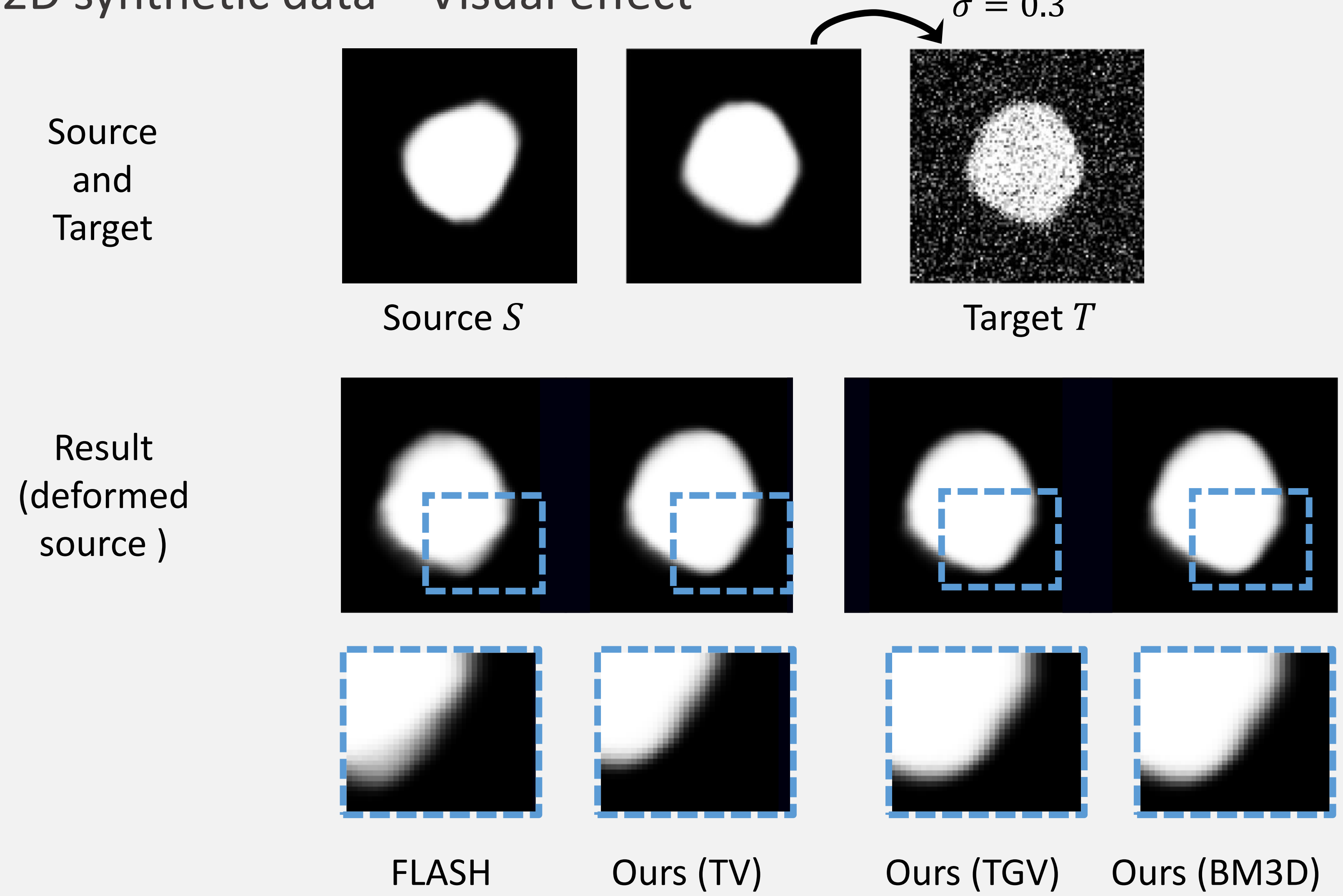


- Algorithm Setting
  - Registration algorithm
    - Fourier-approximated Lie Algebras for Shooting (FLASH)[1]
  - Denoising algorithm
    - Total variation (TV)
    - Total generalized variation (TGV)
    - Block-matching and 3D filtering (BM3D)

[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)

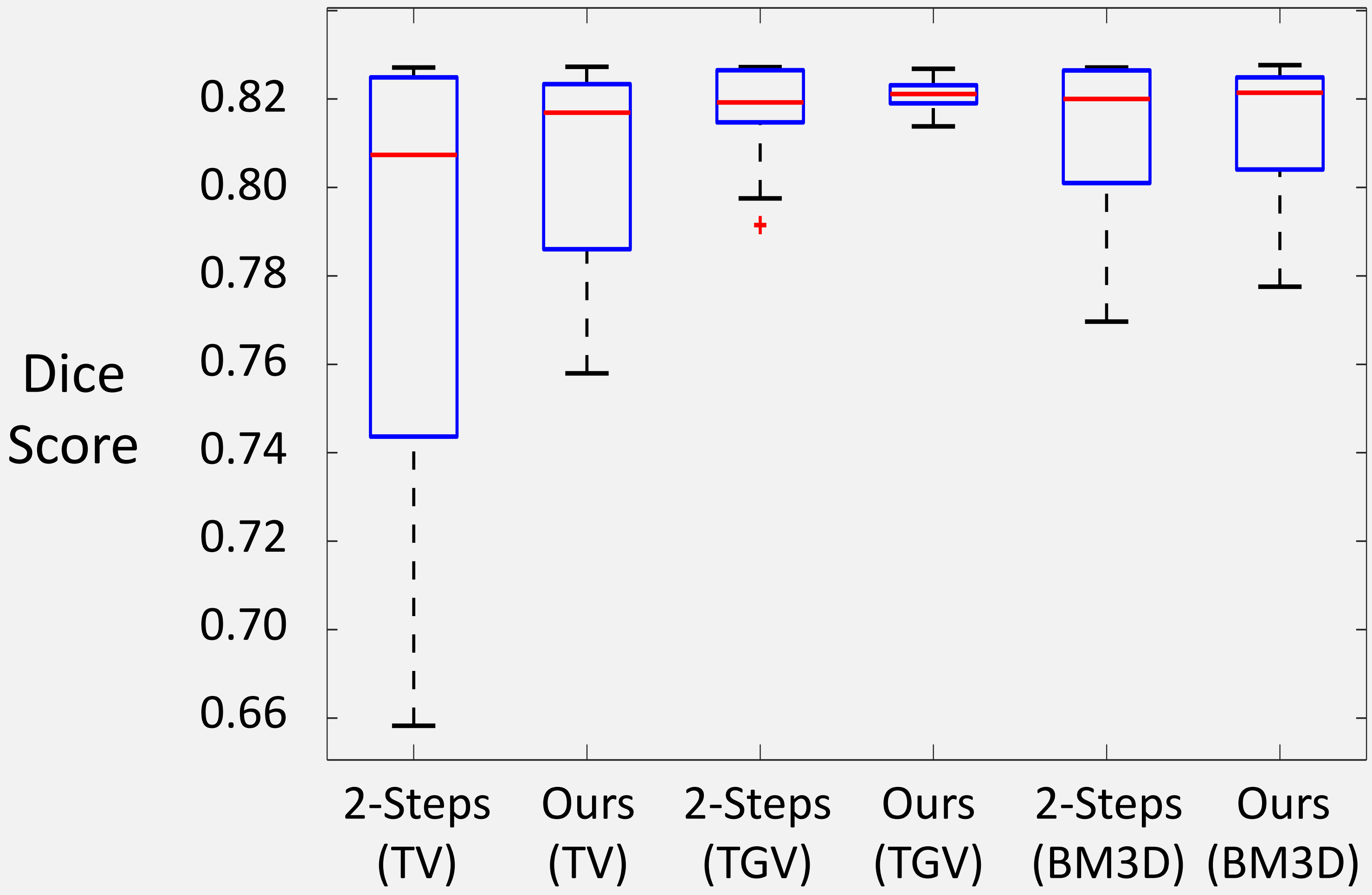
Experiments

- Result
  - 2D synthetic data – Visual effect



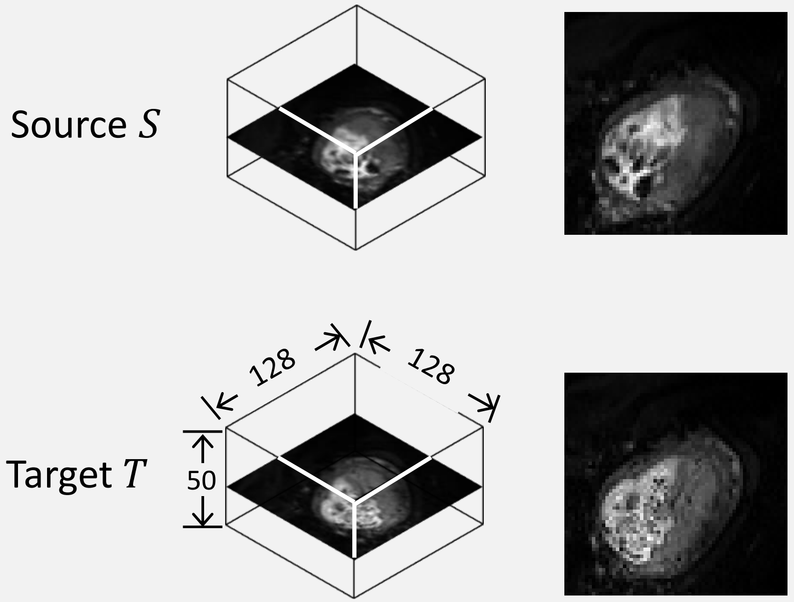
Experiments

- Result
  - 2D synthetic data – Quantitative performance



Experiments

- Data
  - Real 3D DW-MRI data



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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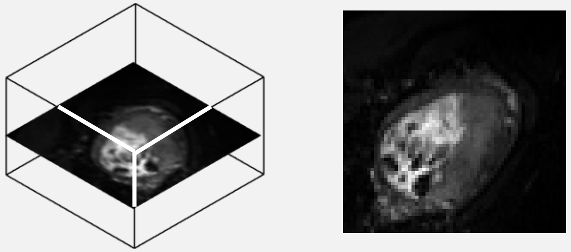
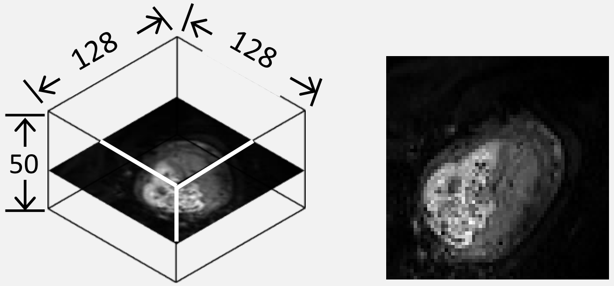


Target T



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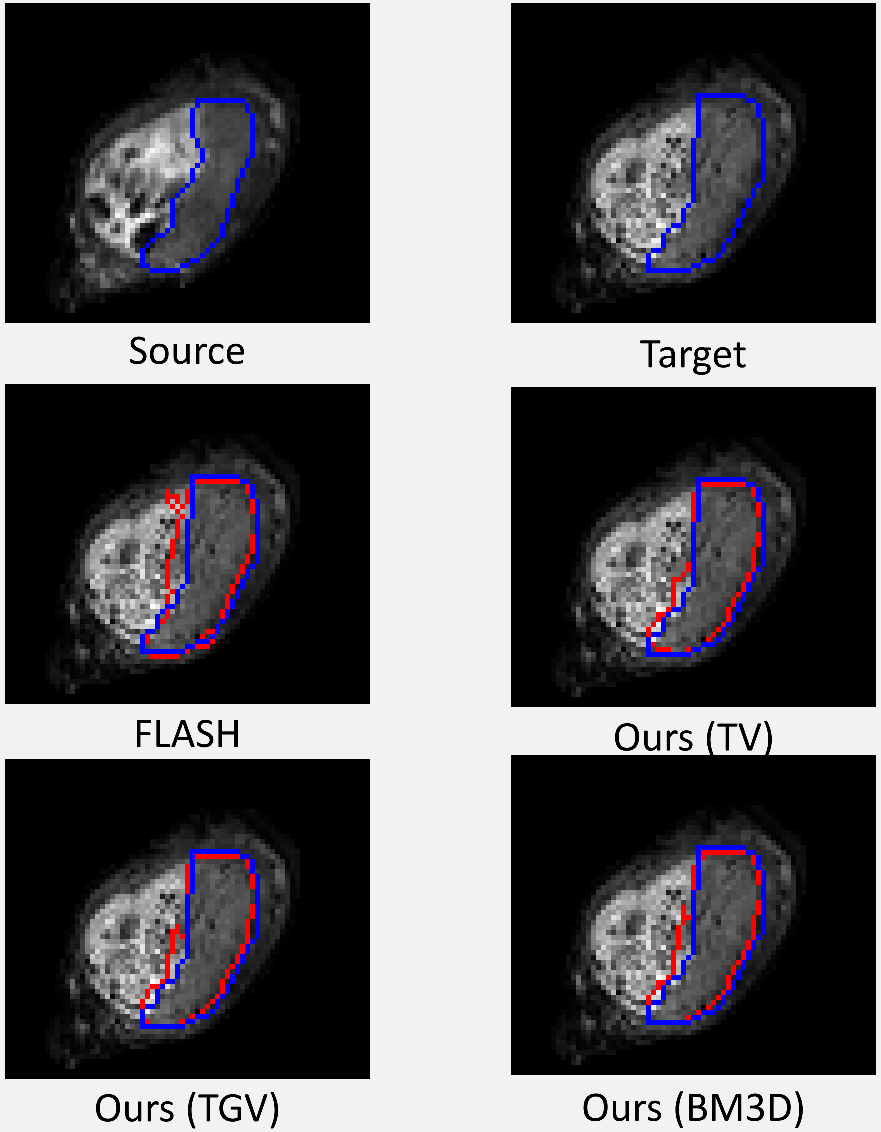
- Result



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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- In contrast to previous approaches, our model has the flexibility to allow arbitrary denoising algorithm integrated with the registration task

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- Questions?

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