



Deep Bilevel Optimization Learning for Medical Image Registration

By: Zi Li

Dalian University of Technology

2022/05/25



Outline

- ① **Background**
- ② **Bilevel Feature Learning for Image Registration**
- ③ **Optimization Learning for Deformable Image Registration**
- ④ **Automated Learning for Medical Image Registration**
- ⑤ **Summary and Outlook**

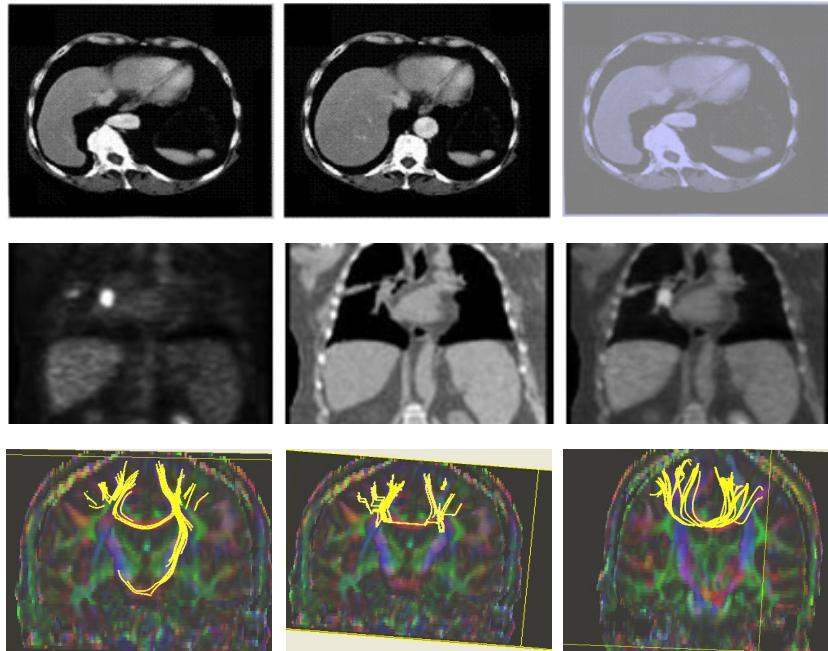


Background

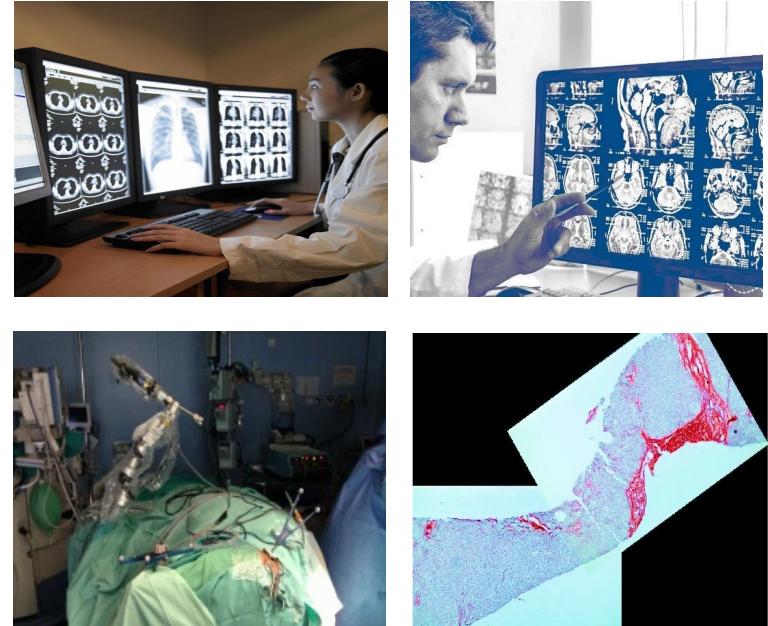
Medical Image Registration (MIR)

Background

Image Registration



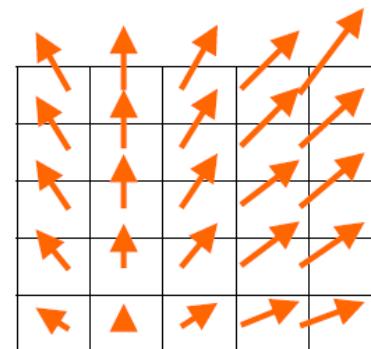
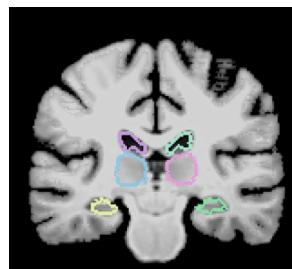
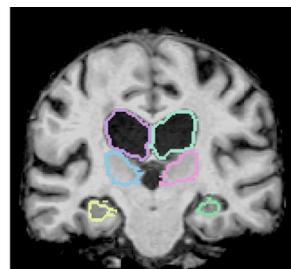
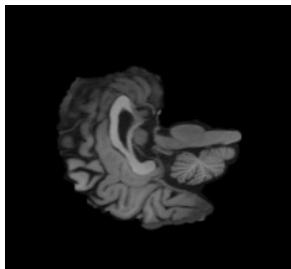
Diagnosis and Surgery



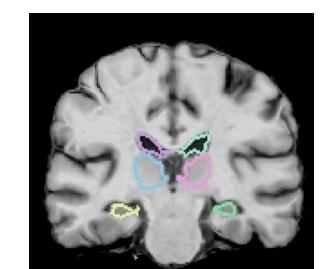
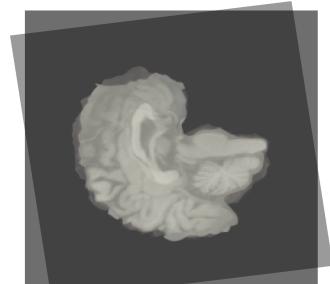
Problem Formulation

■ Objective of deformable registration

$$\min_{\varphi} \underbrace{E_D(\varphi; F, M(\varphi))}_{\text{Data Match}} + \lambda \underbrace{E_R(\varphi)}_{\text{Regularization}}$$



Transformation Field



Moving

Fixed

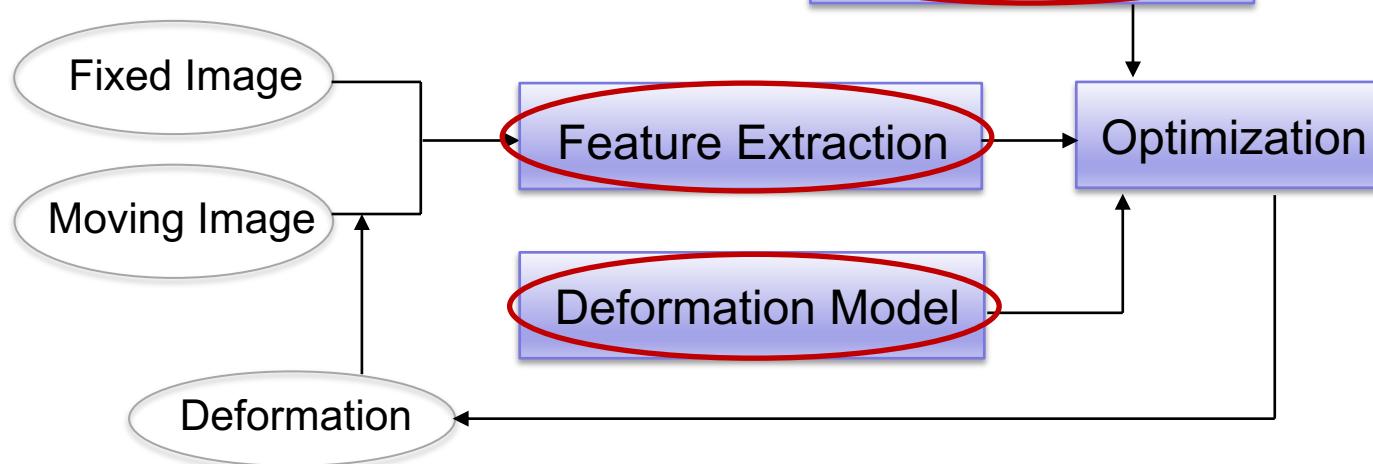
Warped

Problem Formulation

■ Objective of deformable registration

$$\min_{\varphi} \underbrace{E_D(\varphi; F, M(\varphi))}_{\text{Data Match}} + \lambda \underbrace{E_R(\varphi)}_{\text{Regularization}}$$

We need to construct
three key components !



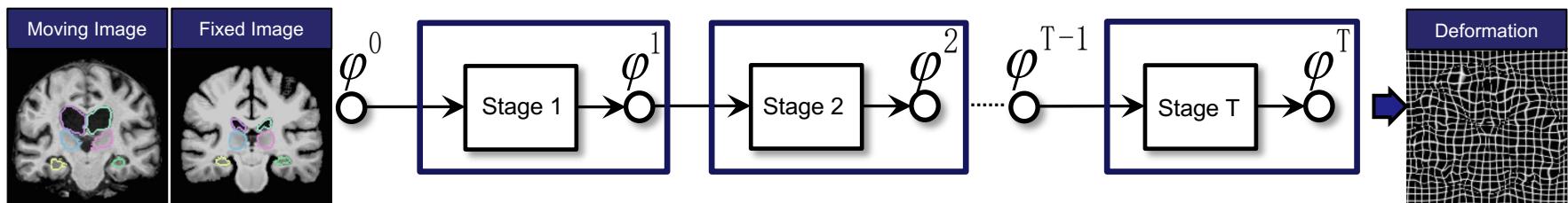
Related Works

■ Optimization based methods

Translate  into knowledge

$$\min_{\varphi} E_D(\varphi; F, M(\varphi)) + \lambda E_R(\varphi)$$

Data Match **Regularization**

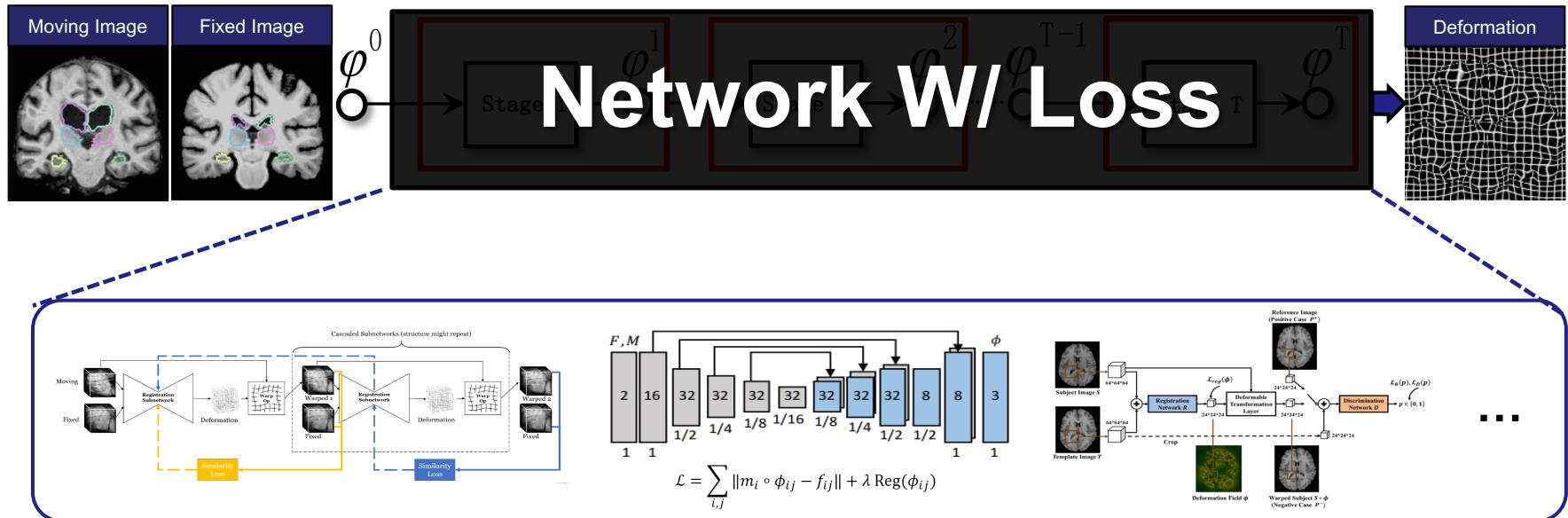


 Satisfying accuracy

 High computational cost

Related Works

■ Deep learning based methods



Fast estimate transformation



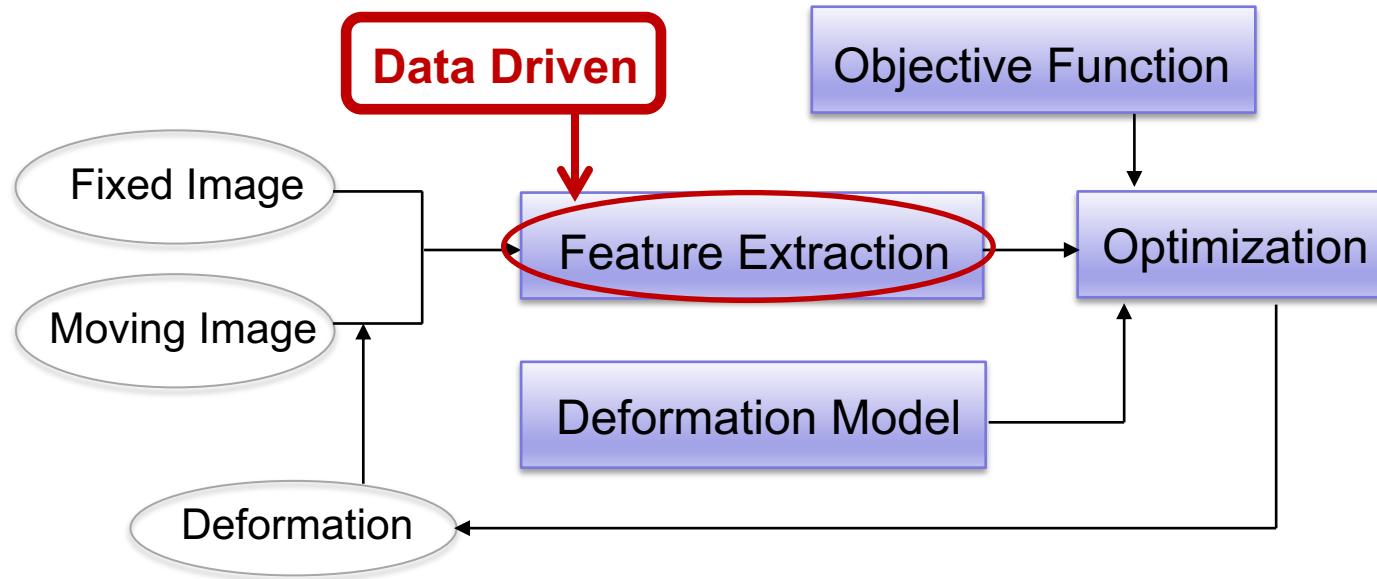
Ignore explicit constraints



Outline

- 1 Background
- 2 **Bilevel Feature Learning for Image Registration**
- 3 Optimization Learning for Deformable Image Registration
- 4 Automated Learning for Medical Image Registration
- 5 Summary and Outlook

Motivation



Feature Learning for MIR

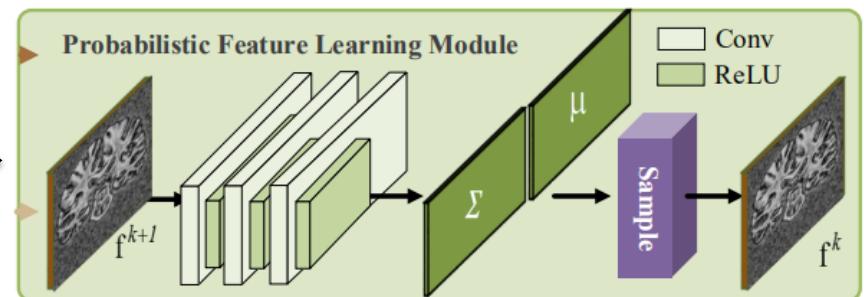
- **Upper-level:** Optimization of Deformable Registration
Lower-level: Probabilistic Feature Learning (**constraint**)

$$\min_{\varphi} E_D(\varphi; f_s, f_t) + E_R(\varphi),$$

$$s.t. \quad f_s, f_t = \arg \max_{f_s, f_t} p(f_s | I_s, f_t | I_t, \varphi).$$

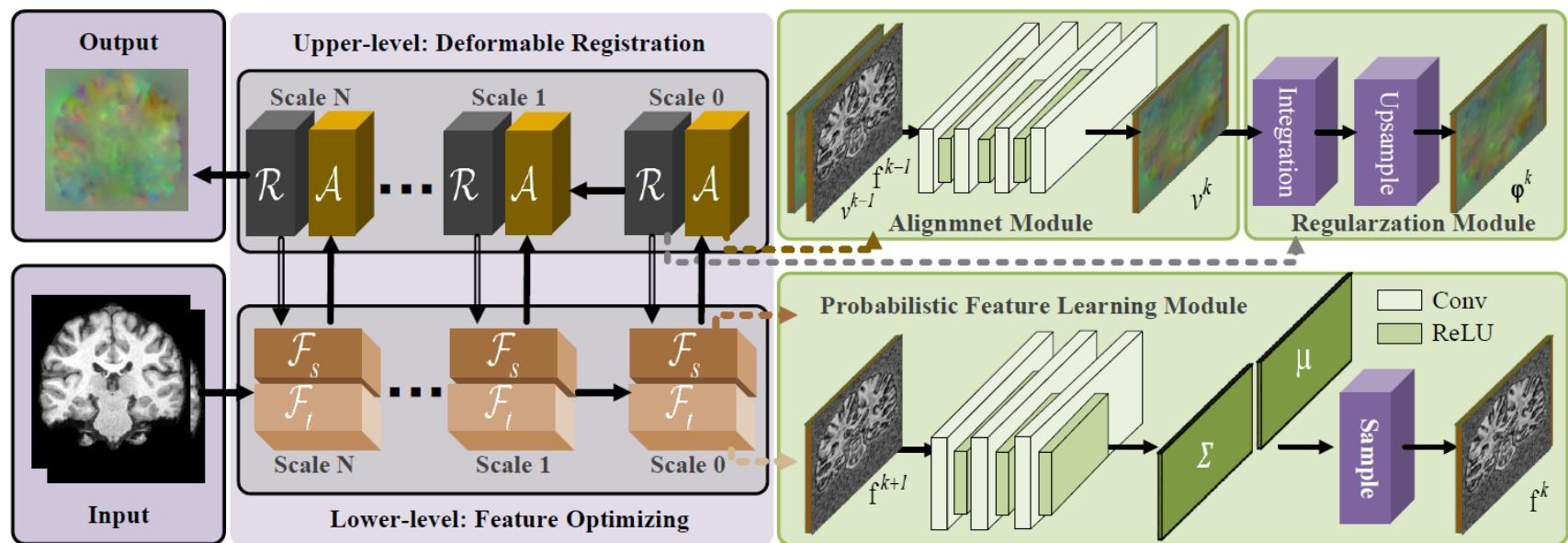
- **Probabilistic Feature Learning Module**

$$\begin{aligned} f &= \arg \min_f \ln p(f | I, \varphi) \\ &= \arg \min_f \underbrace{\ln p(I | f, \varphi)}_{\text{Data Likelihood}} + \underbrace{\ln p(f)}_{\text{Prior}} \end{aligned}$$



Feature Learning for MIR

- Our Paradigm



Loss Function

Feature space: $l_{KL}(\mu, \Sigma) = 1/2 \left(\text{tr}(\Sigma) + \|\mu\| - \log \det(\Sigma) - m \right)$

Image space: $l(I_s, I_t; \varphi) = l_{NCC}(I_s \circ \varphi, I_t) + l_{\text{smooth}}(\varphi)$.



Feature Learning for MIR

◆ Quantitative comparison

Dice score	Elastix ^[1]	NiftyReg ^[2]	ANTs ^[3]	VM ^[4]	VM-diff ^[5]	Ours
OASIS	0.709	0.748	0.765	0.765	0.757	0.777
ABIDE	0.699	0.747	0.728	0.754	0.773	0.764
ADNI	0.697	0.737	0.761	0.761	0.768	0.773
PPMI	0.730	0.765	0.778	0.775	0.781	0.787

Runtime (s)	Elastix	NiftyReg	ANTs	VM	VM-diff	Ours
Img-to-Atlas	90	486	4529	0.615	0.512	0.351

[1] Elastix: A toolbox for intensity-based medical image registration.

[2] Free-form deformation using lower-order B-spline for nonrigid image registration.

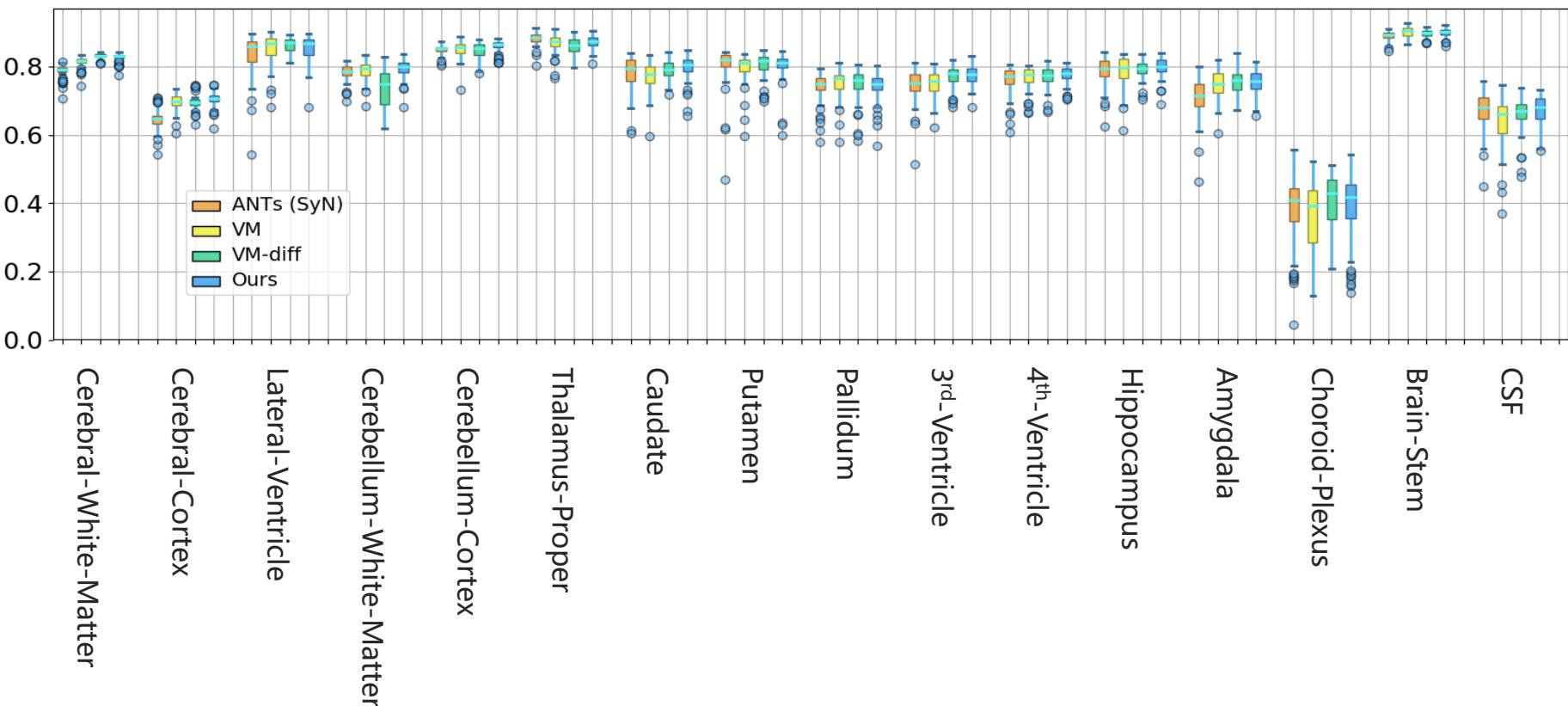
[3] A reproducible evaluation of ants similarity metric performance in brain image registration.

[4] Voxelmorph: A learning framework for deformable medical image registration.

[5] Unsupervised learning of probabilistic diffeomorphic registration for images and surfaces.

Feature Learning for MIR

◆ Visualizations of Dice score

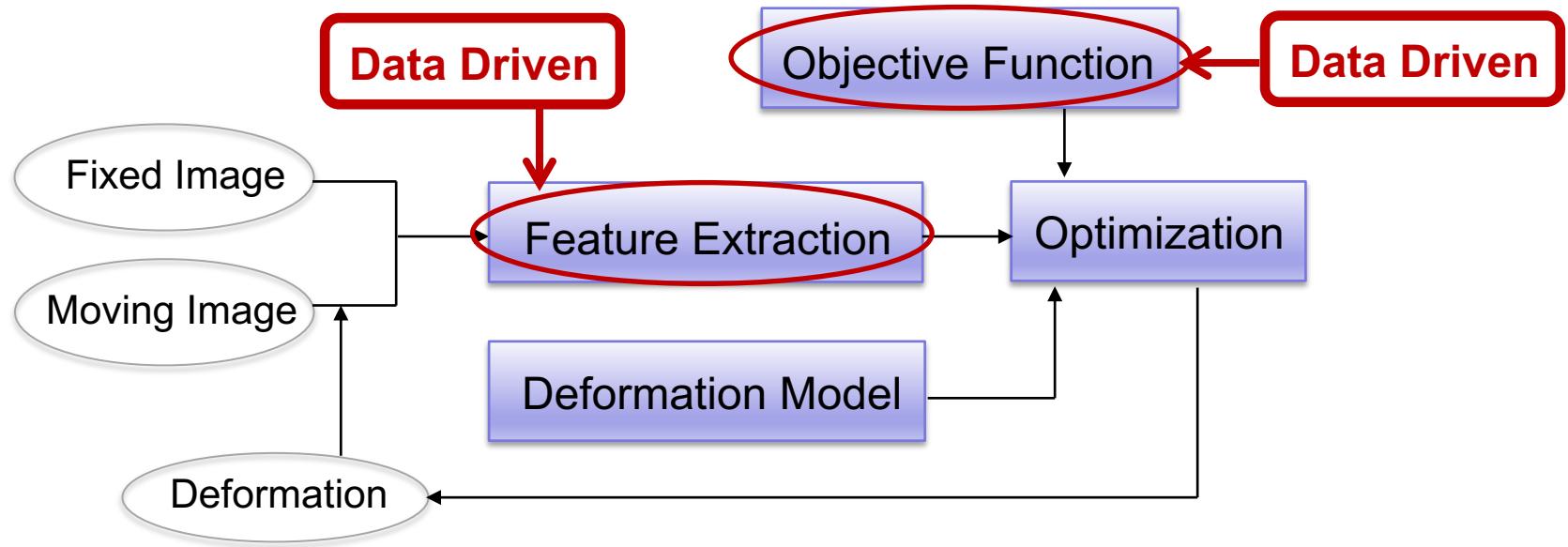




Outline

- 1 Background
- 2 Bilevel Feature Learning for Image Registration
- 3 Optimization Learning for Deformable Image Registration
- 4 Automated Learning for Medical Image Registration
- 5 Summary and Outlook

Motivation



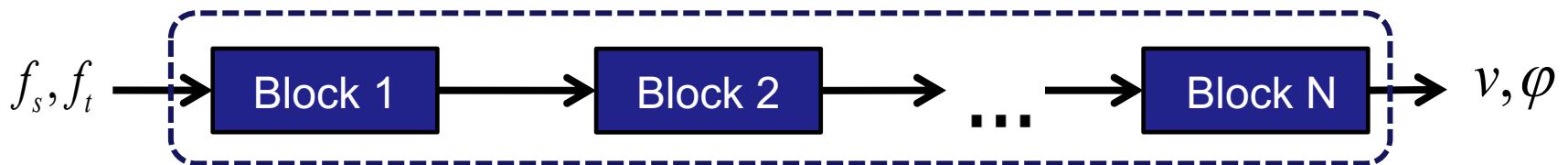


Optimization Learning for MIR

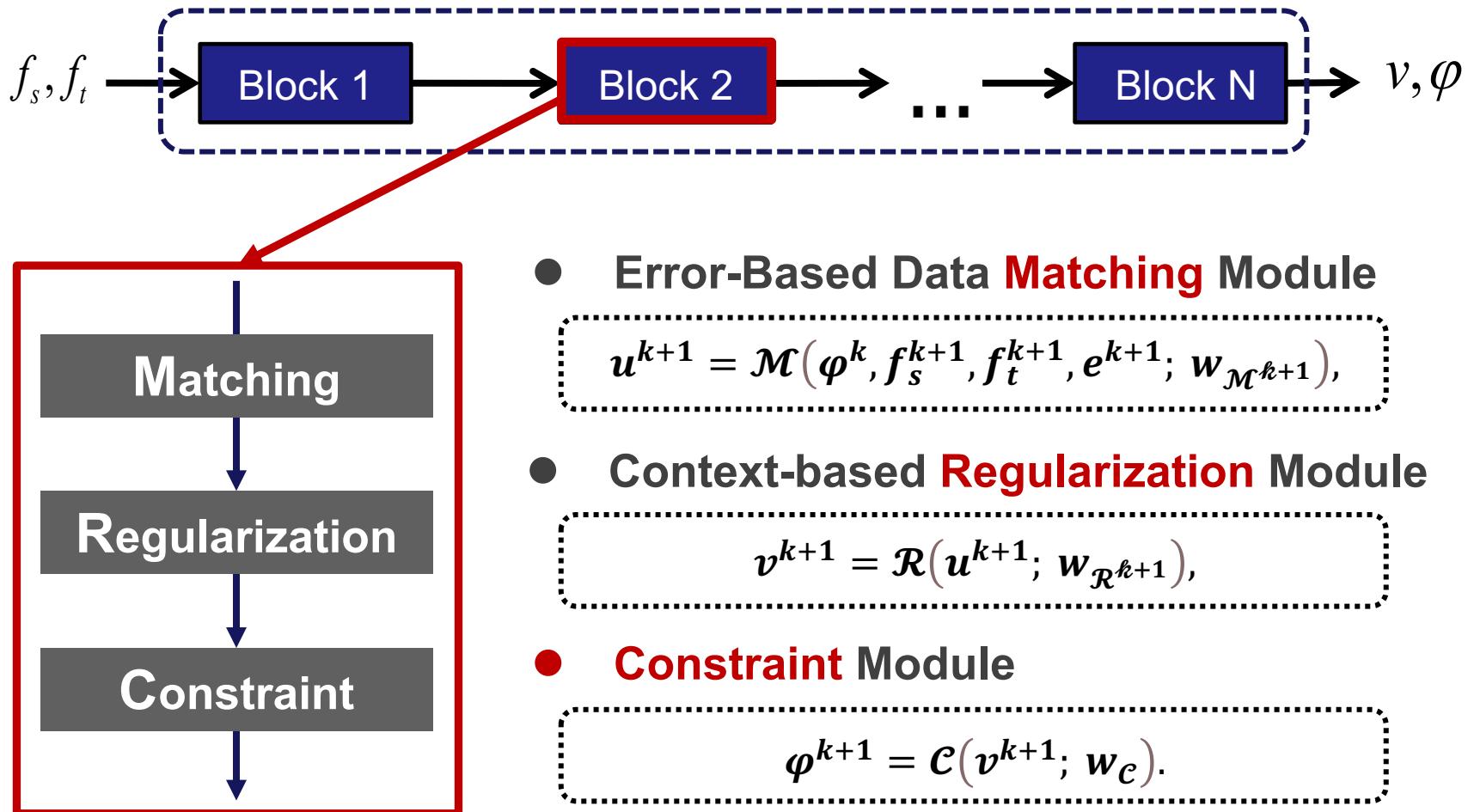
- Fundamental Optimization Formulation of Diffeomorphic Deformable Registration

$$\begin{aligned} & \min_{\nu} \underbrace{\text{Mat}(\varphi \circ s, t)}_{\text{Data Match}} + \lambda \underbrace{\text{Reg}(\nu)}_{\text{Regularization}}, \\ & \text{s. t. } \underbrace{\frac{\partial \phi(t)}{\partial t} = \nu(\phi(t)), \phi(0) = Id, \phi = \phi(1)}_{\text{Constraint}}. \end{aligned}$$

- Deep Propagation on Feature Space *in Sec.2*

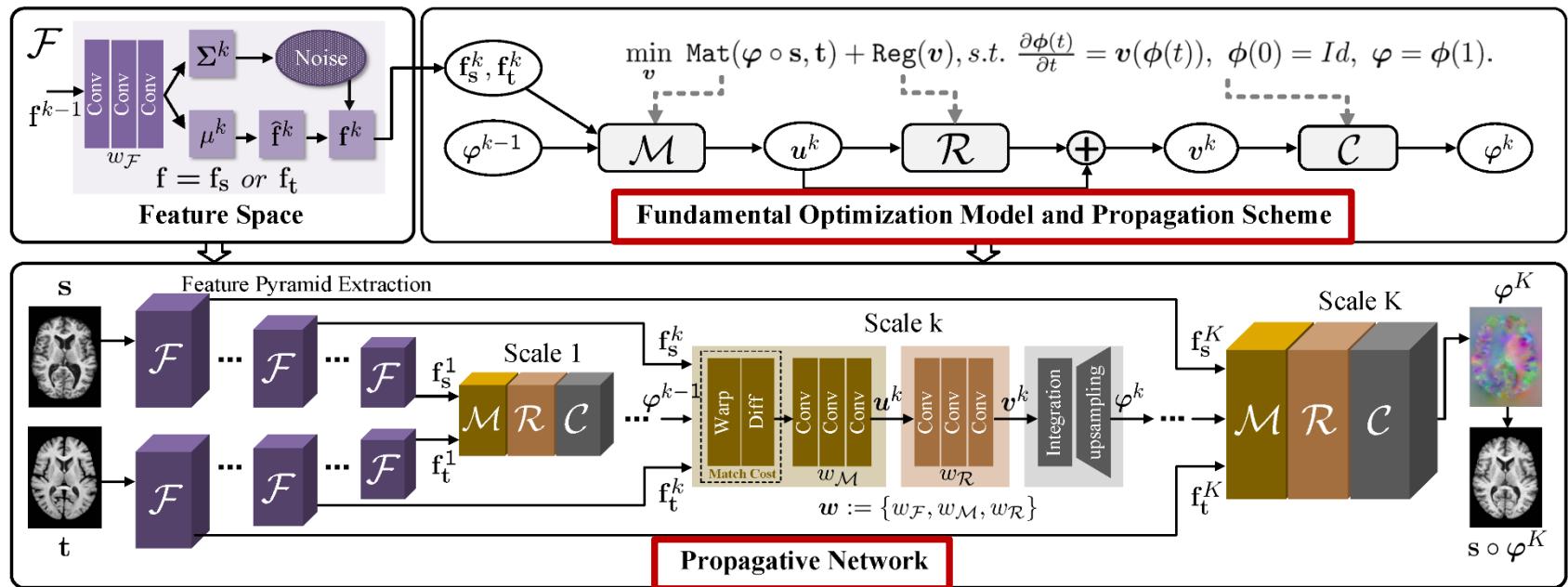


Optimization Learning for MIR



Optimization Learning for MIR

- Learning Registration from Optimization on Feature Space in Sec.2

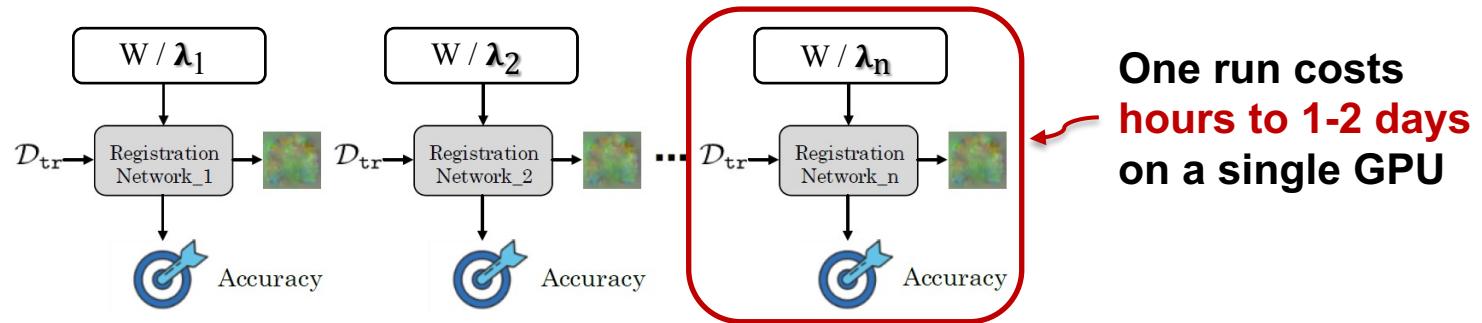


Objective

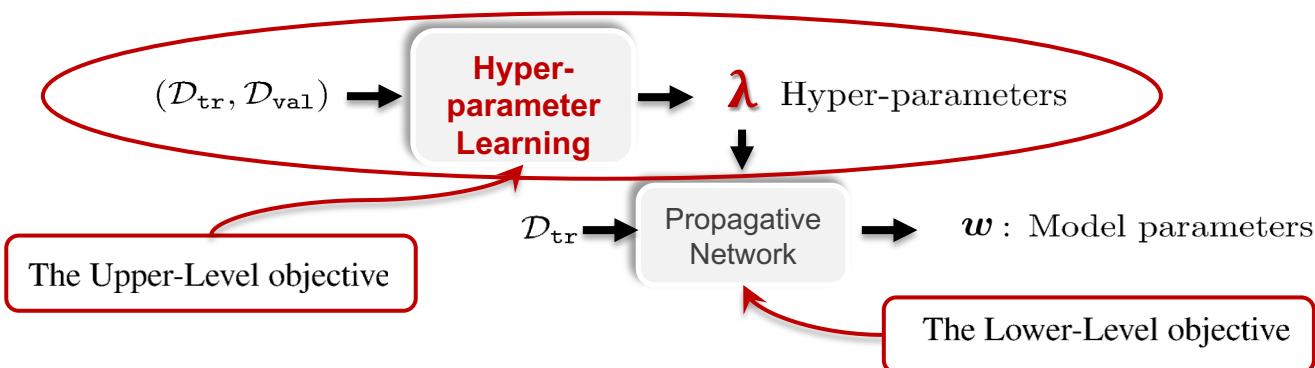
$$l(w(\lambda), s_i, t_i) = \sum_0^K \lambda_{sta}^k \left(l_{KL}(\mu^k, \Sigma^k) + \lambda_{mat} l_{mat}(s_i \circ \varphi^k, t_i) + \lambda_{reg} l_{reg}(v^k) \right)$$

Optimization Learning for MIR

■ Conventional Objective Choosing through Many Training Runs

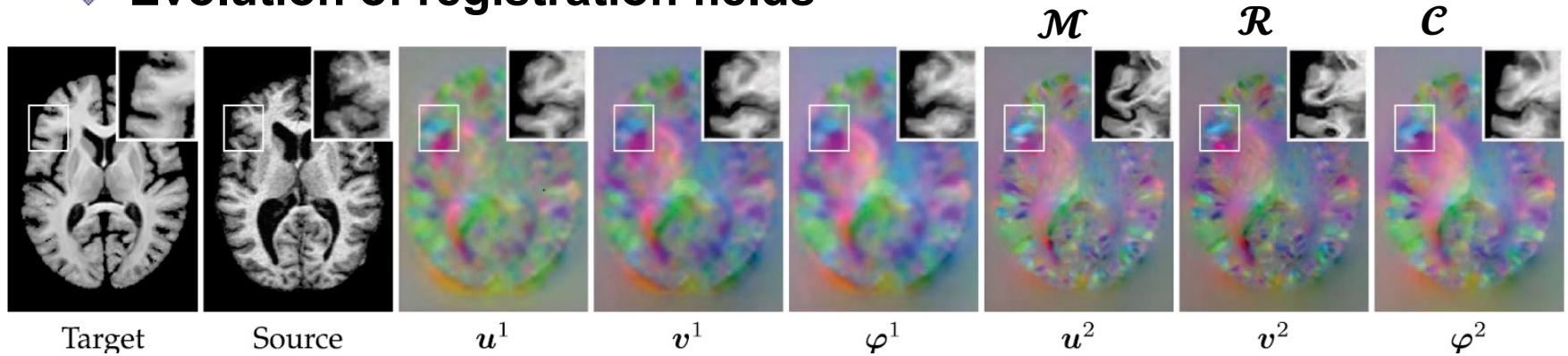


● Bilevel Self-tuned Training for λ

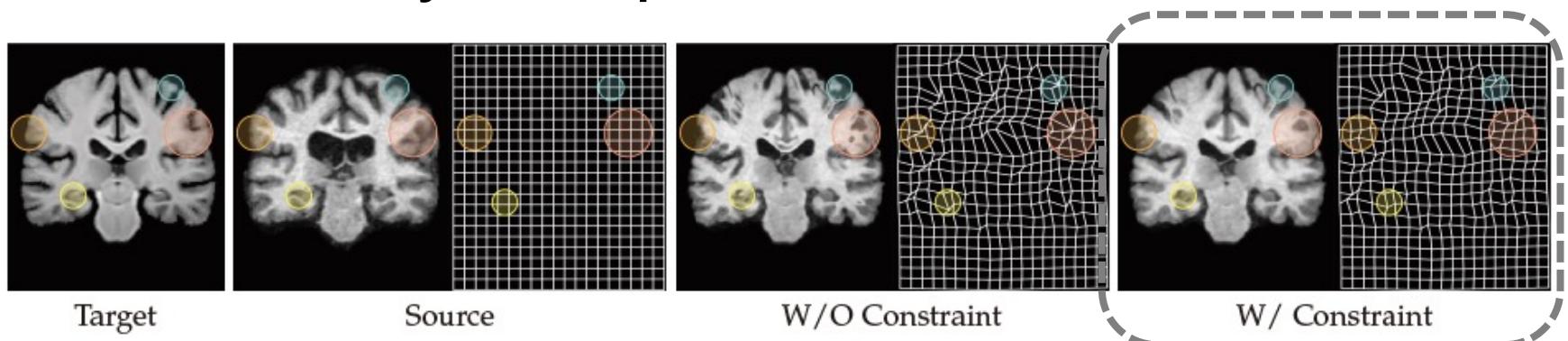


Optimization Learning for MIR

- ◆ Evolution of registration fields



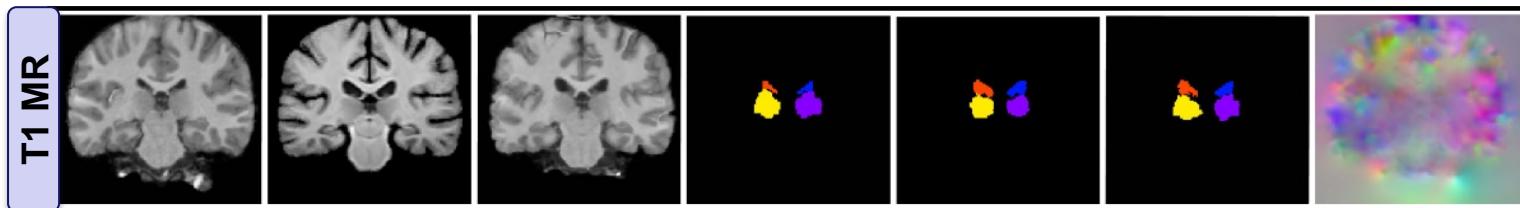
- ◆ Ablation analysis of explicit constraints



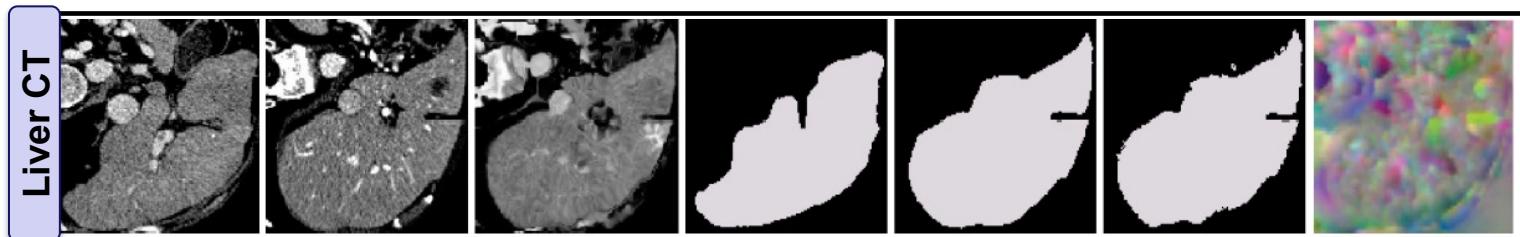
Optimization Learning for MIR

- ◆ Searched hyperparameters for three tasks

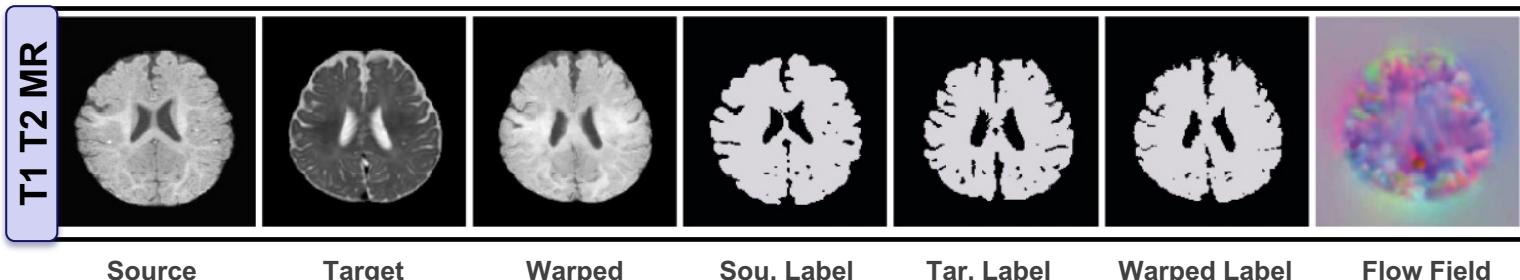
$$W / \lambda = 1.6$$



$$W / \lambda = 1.2$$

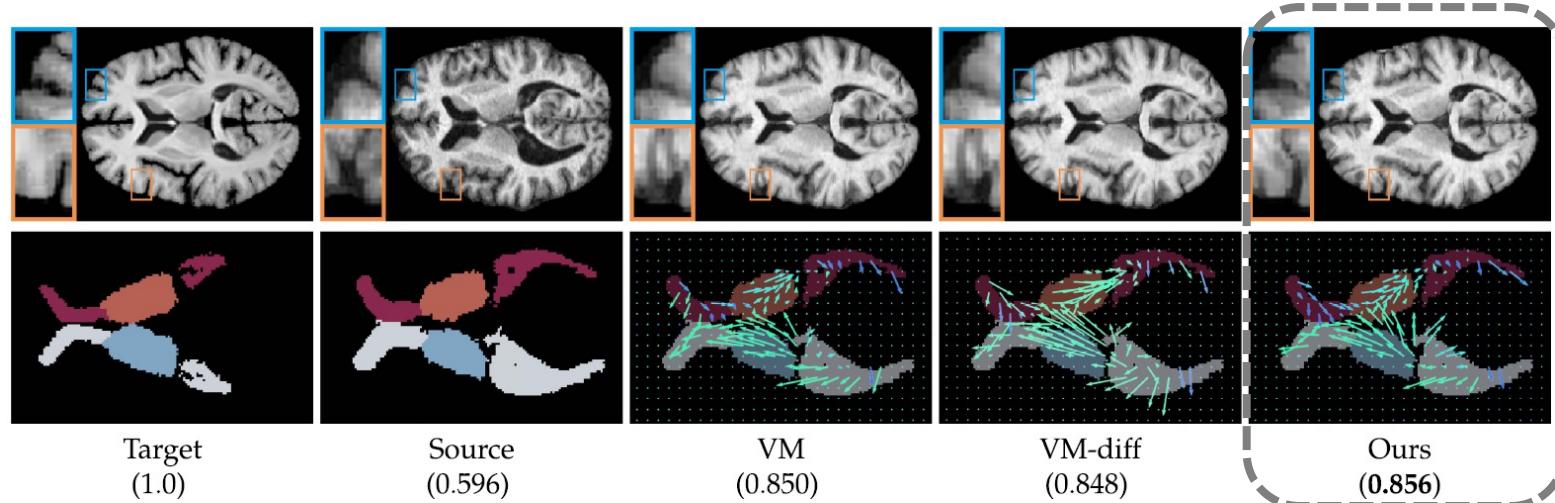
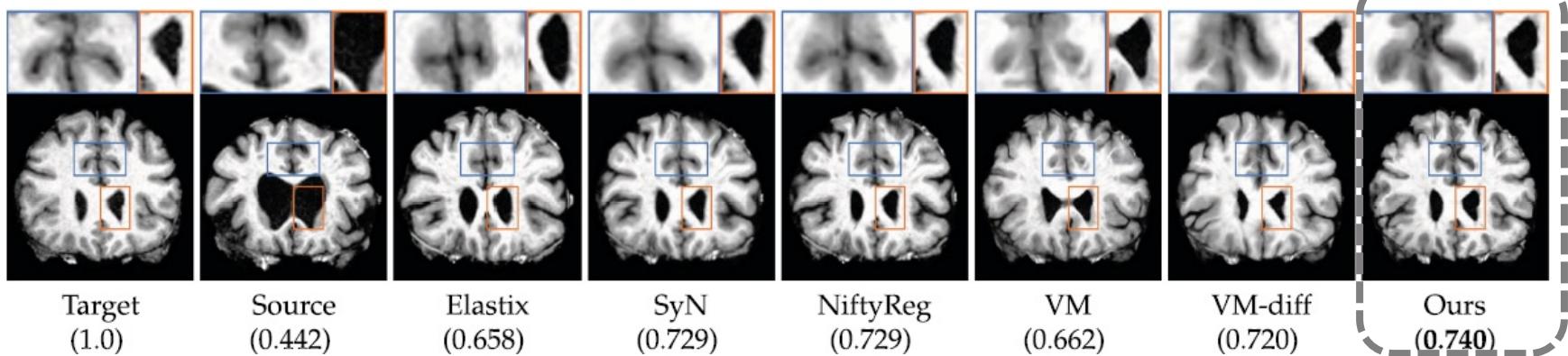


$$W / \lambda = 0.1$$



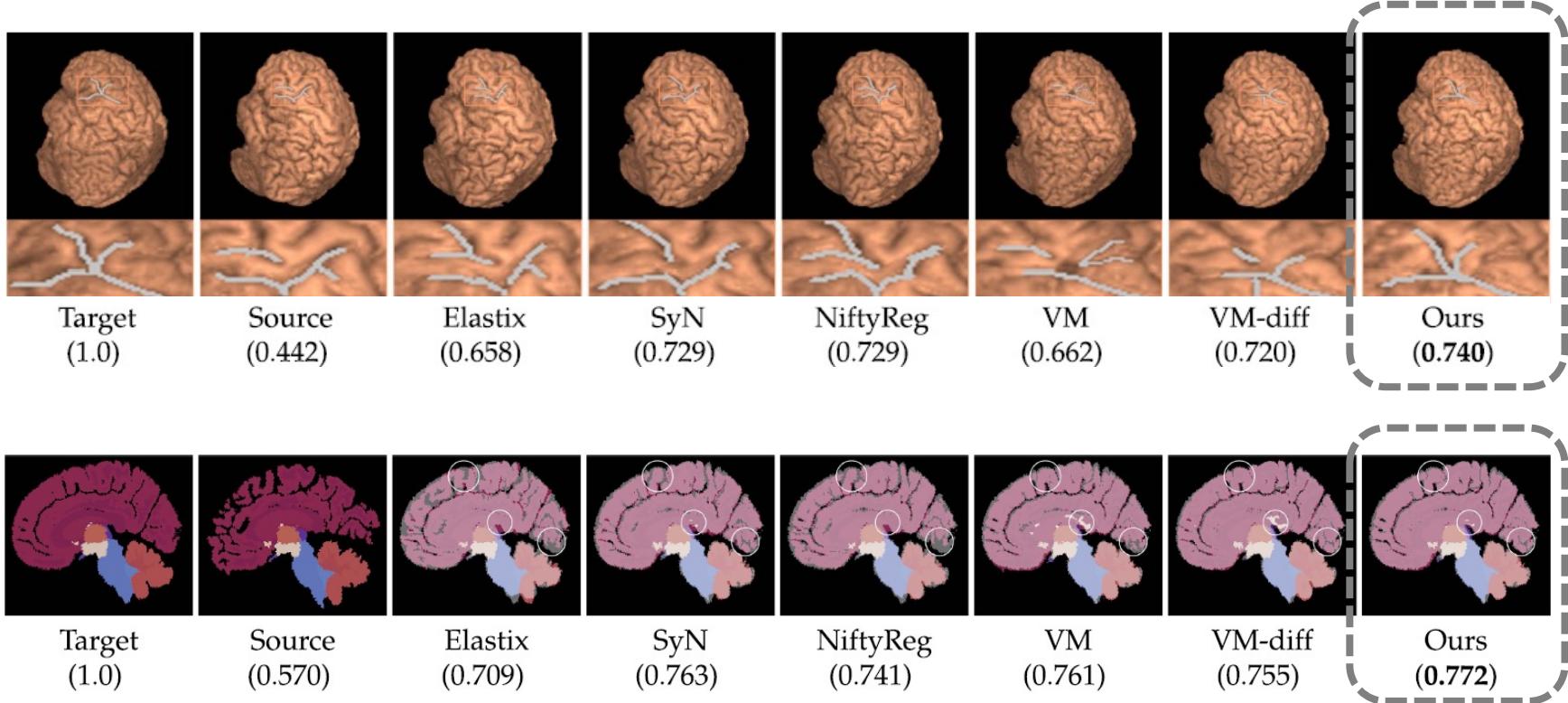
Optimization Learning for MIR

◆ Qualitative comparisons



Optimization Learning for MIR

◆ Qualitative comparisons

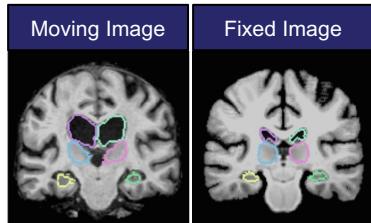
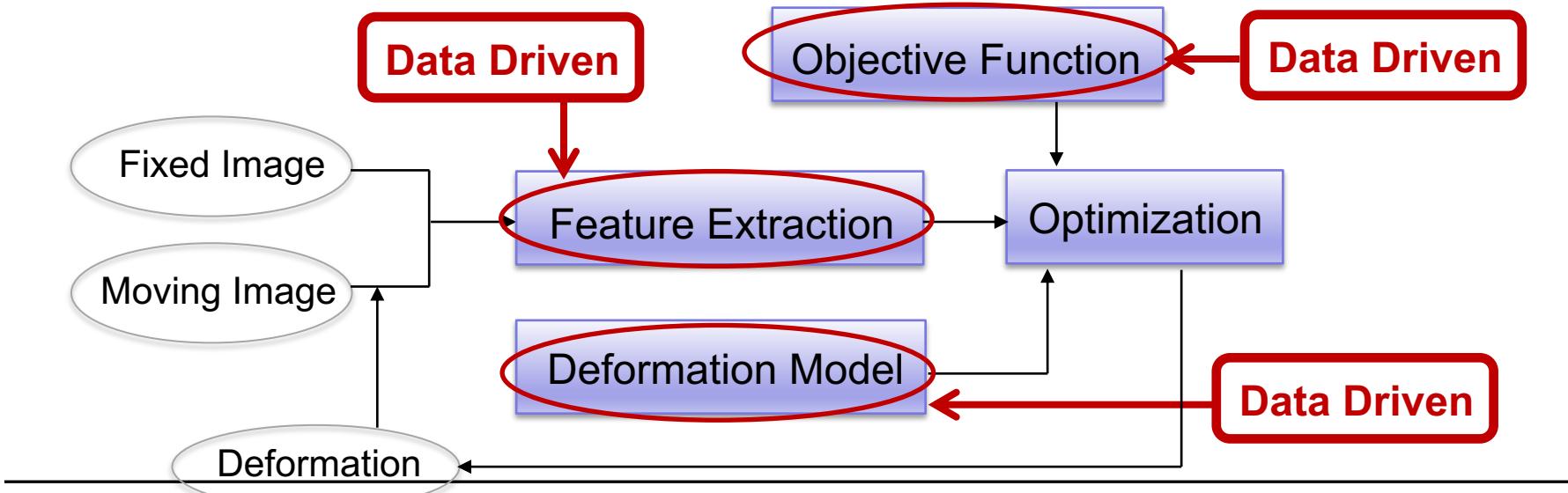




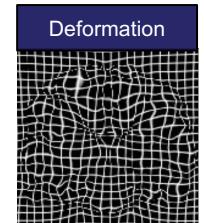
Outline

- 1 Background
- 2 Bilevel Feature Learning for Image Registration
- 3 Optimization Learning for Deformable Image Registration
- 4 **Automated Learning for Medical Image Registration**
- 5 Summary and Outlook

Motivation



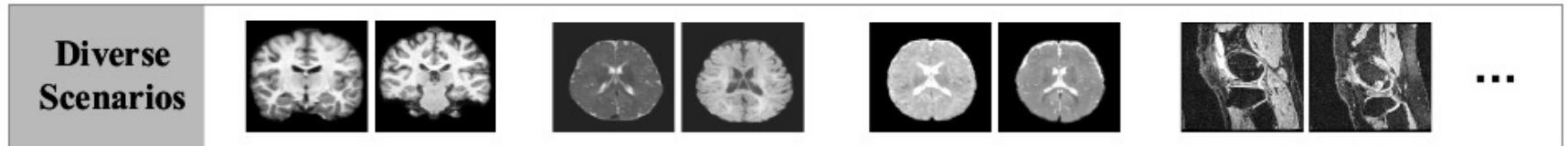
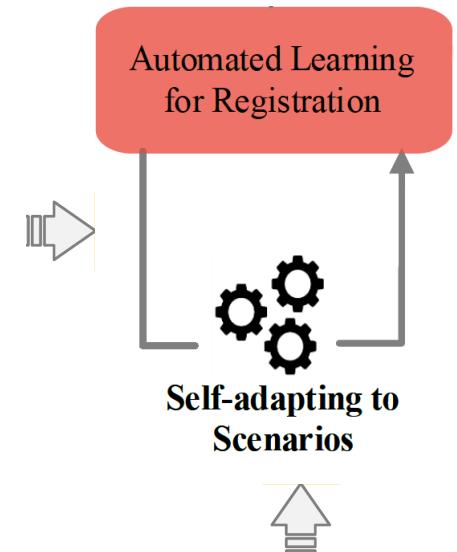
- ✓ **No Rely on Expertise**
- ✓ **Low Validation Costs**



Automated Learning for MIR

- Triple-level Optimization for AutoReg

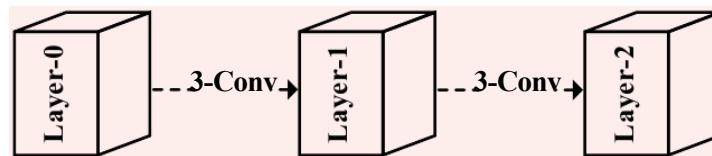
$$\begin{aligned}
 & \min_{\lambda} \mathcal{L}_{val}^{seg}(\lambda, \alpha^*, \omega^*; s, t), \\
 \text{s.t. } & \left\{ \begin{array}{l} \alpha^*(\lambda) = \arg \min_{\alpha} \mathcal{L}_{val}^{reg}(\alpha, \omega^*(\alpha); \lambda, s, t), \\ \text{s.t. } \omega^*(\alpha) = \arg \min_{\omega} \mathcal{L}_{tr}^{reg}(\omega; \alpha, \lambda, s, t). \end{array} \right.
 \end{aligned}$$



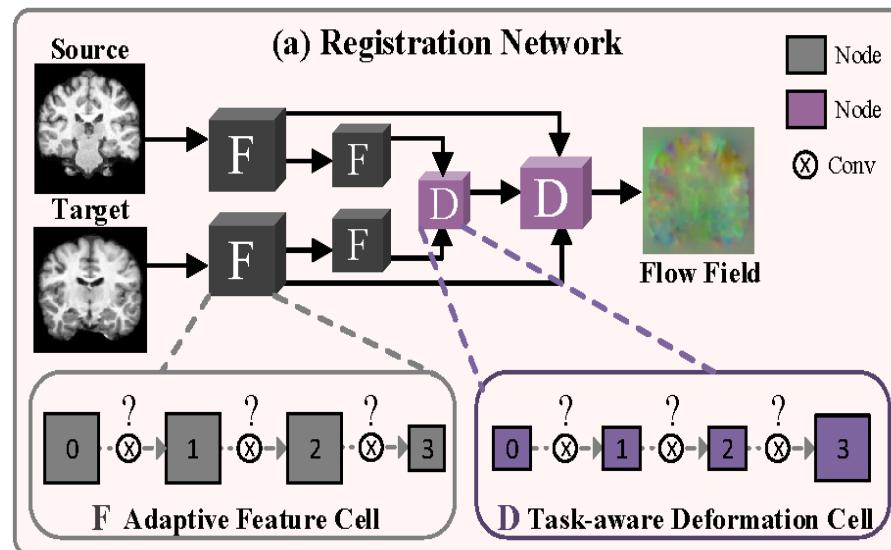
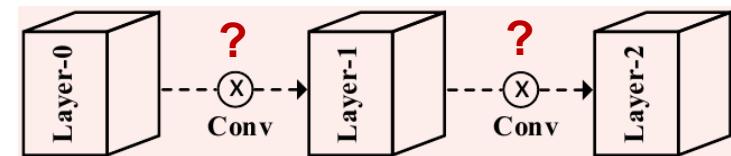
Automated Learning for MIR

- Architecture Search: From Hand-design to Search

From



to



Search Space

- $1 \times 1 \times 1$ Conv (1-Conv)
- $3 \times 3 \times 3$ Conv (3-Conv)
- $5 \times 5 \times 5$ Conv (5-Conv)
- $3 \times 3 \times 3$ Separable Conv (3-SConv)
- $5 \times 5 \times 5$ Separable Conv (5-SConv)
- $3 \times 3 \times 3$ Dilation Conv (3-DConv)
- $5 \times 5 \times 5$ Dilation Conv (5-DConv)
- $7 \times 7 \times 7$ Dilation Conv (7-DConv)



Automated Learning for MIR

◆ Optimality verification across registration tasks

Method	Brain T1-to-T1	Brain T2-to-T2	Knee T1-to-T1	Brain T2-to-T1
All-1-Conv	0.700 (0.035)	0.610 (0.009)	0.395 (0.110)	0.579 (0.005)
All-3-Conv	0.769 (0.025)	0.636 (0.010)	0.605 (0.131)	0.617 (0.006)
All-7-Conv	0.761 (0.025)	0.610 (0.009)	0.614 (0.091)	0.613 (0.007)
AutoReg	0.778 (0.023)	0.646 (0.010)	0.616 (0.150)	0.622 (0.007)

◆ Computation cost

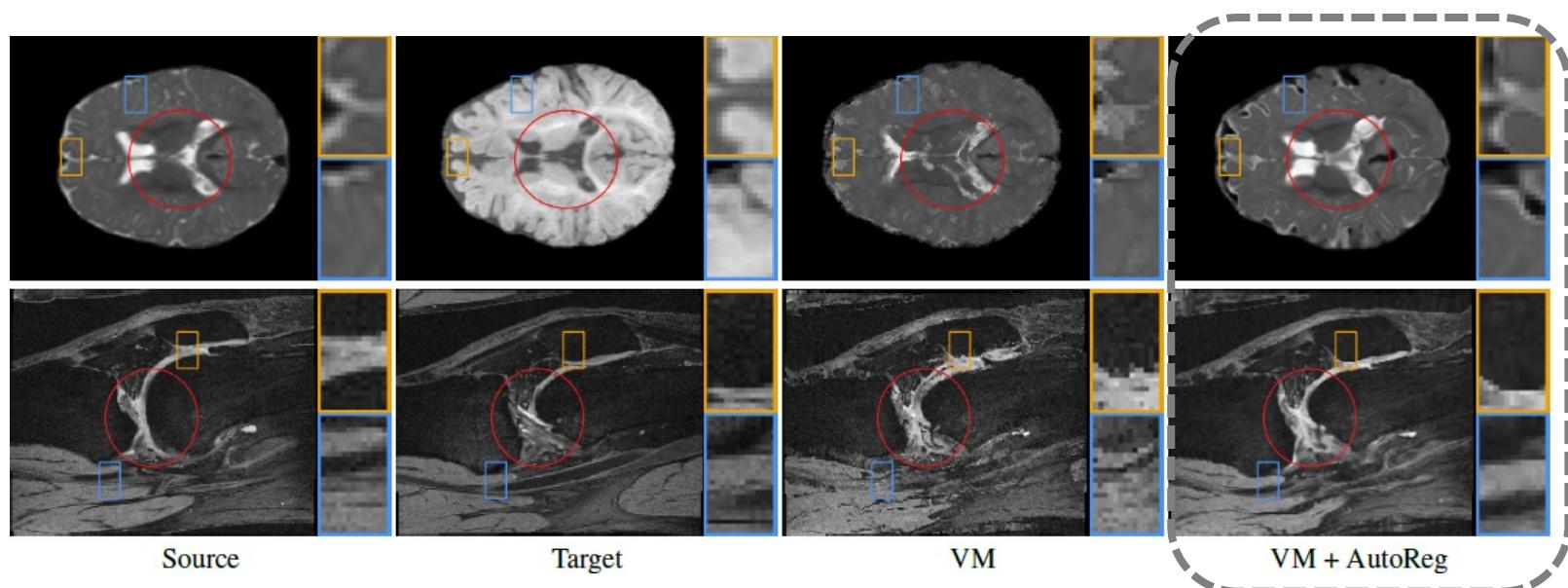
Strategy	AutoReg + Training	Manual + Training
Runtime	48 + 23 hour	23 * n + 23 hour

Typically set **larger than 10**

Automated Learning for MIR

◆ Generalizability analysis

Method	Brain T1-to-T1	Brain T2-to-T2	Knee T1-to-T1	Brain T2-to-T1
VM	0.757 (0.035)	0.638 (0.012)	0.440 (0.132)	0.579 (0.013)
VM + AutoReg	0.761 (0.010)	0.640 (0.013)	0.482 (0.151)	0.596 (0.006)



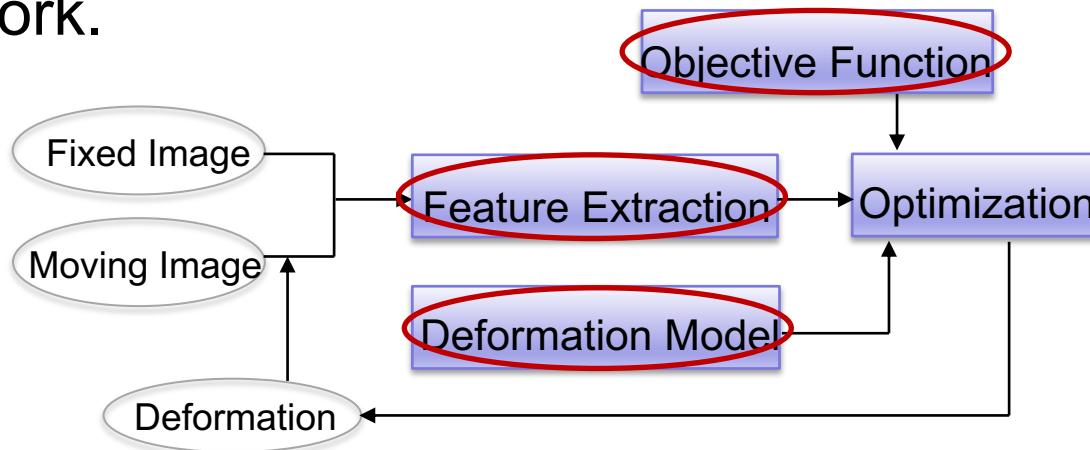


Outline

- 1 Background
- 2 Bilevel Feature Learning for Image Registration
- 3 Optimization Learning for Deformable Image Registration
- 4 Automated Learning for Medical Image Registration
- 5 Summary and Outlook

Summary

- Integrates **deep learning** with **bilevel optimization** and proposes algorithms from **three aspects** of registration framework.



- **Feature learning-based** bi-level optimization model
- Novel similarity measurement, bilevel **self-tuned loss function**
- Automated optimization of the **loss function** and **architecture** of feature/deformation learning modules



Future Work

□ Auto Learning for Registration

$$\begin{aligned} & \min_{\lambda} \mathcal{L}_{val}^{seg}(\lambda, \alpha^*, \omega^*; s, t), \\ \text{s.t. } & \left\{ \begin{array}{l} \alpha^*(\lambda) = \arg \min_{\alpha} \mathcal{L}_{val}^{reg}(\alpha, \omega^*(\alpha); \lambda, s, t), \\ \text{s.t. } \omega^*(\alpha) = \arg \min_{\omega} \mathcal{L}_{tr}^{reg}(\omega; \alpha, \lambda, s, t). \end{array} \right. \end{aligned}$$

Cover other architectural hyperparameters

- network topology that controls the connections among cells
- number of layers and resolution levels
- ...



Acknowledgment

◆ Natural Science Foundation of China

◆ Faculty members

- **Xin Fan**—Professor, Dalian University of Technology
- **Risheng Liu**—Professor, Dalian University of Technology
- **Adrian Vasile Dalca**—Assistant Professor, Harvard Medical School
- **Huang Hao**—Professor, University of Pennsylvania

◆ Students

- **Yuxi Zhang**—Dalian University of Technology
- **Ziyang Li**—Dalian University of Technology

...



Thanks !

