面向医学影像配准的深度双层优化学习

报告人：李 孜

2022年07月15日

目录

- 研究背景
- 基于双层特征学习的配准
- 基于优化学习的可变形配准
- 基于自动机器学习的配准
- 总结与展望

第一章

研究背景

Research background

研究意义

- 面向 **生命健康** 的 **医学影像配准**

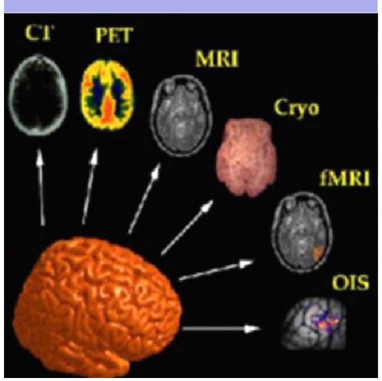
配准

- 不同的模态
- 不同的时间
- 不同的患者

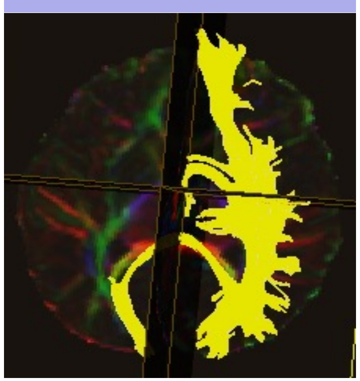
→

- □ 信息融合
- □ 时序分析
- □ 微创手术引导
- □ 图谱构建

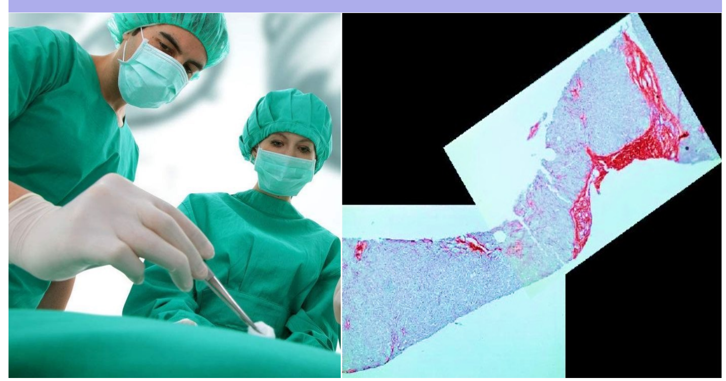
信息融合



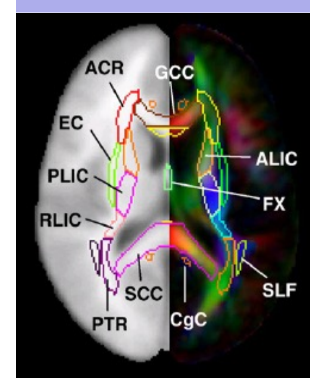
时序分析



微创手术引导



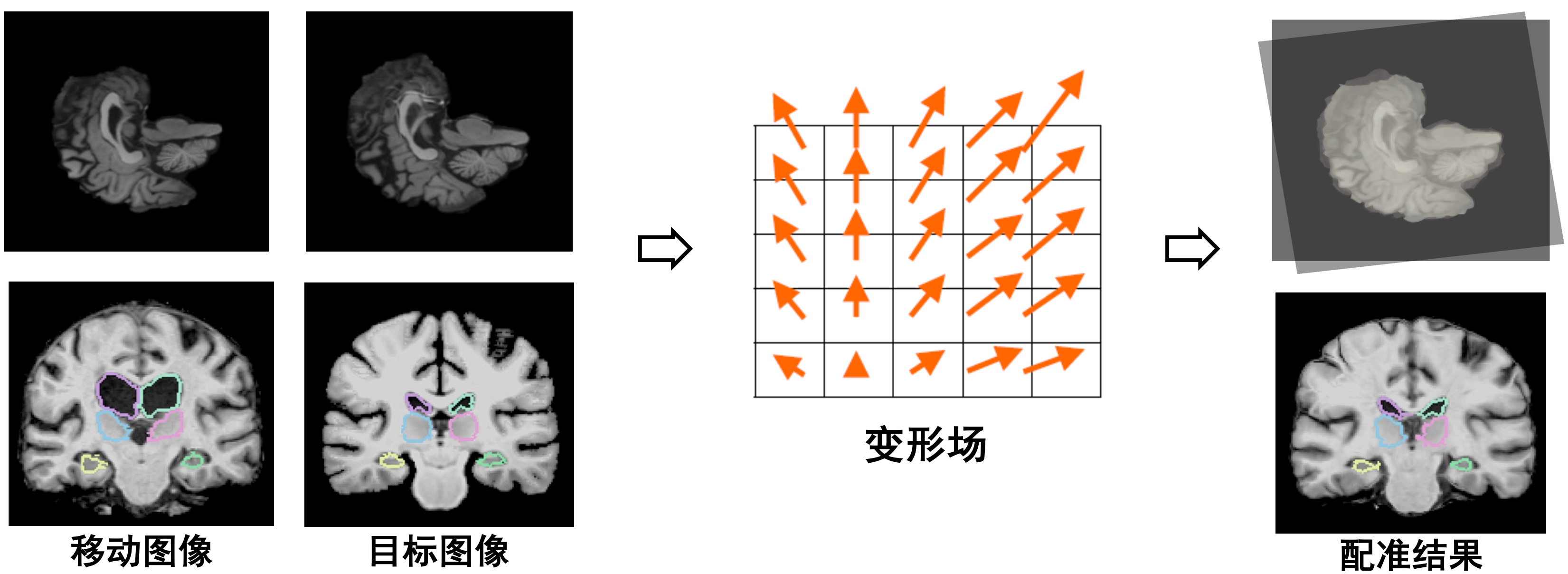
图谱构建



问题建模

■ 配准的 **优化目标** 如下

$$\min_{\varphi} \underbrace{E_D\big(\varphi; F, M(\varphi)\big)}_{\text{数据匹配项}} + \lambda \underbrace{E_R(\varphi)}_{\text{正则项}}$$



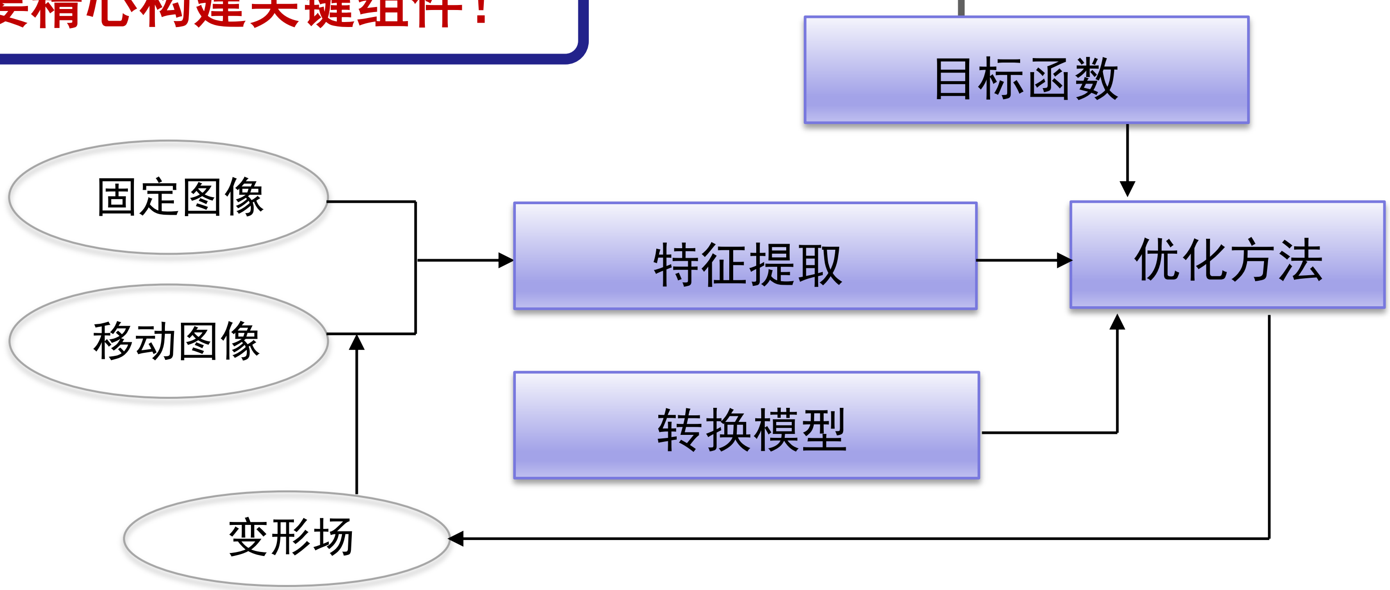
DAMO
ALIBABA DAMO ACADEMY

问题建模

■ **配准的 优化目标 如下**

$$\min_{\varphi} \underbrace{E_D\left(\varphi; F, M(\varphi)\right)}_{\text{数据匹配项}} + \lambda \underbrace{E_R(\varphi)}_{\text{正则项}}$$

需要精心构建关键组件！



相关工作

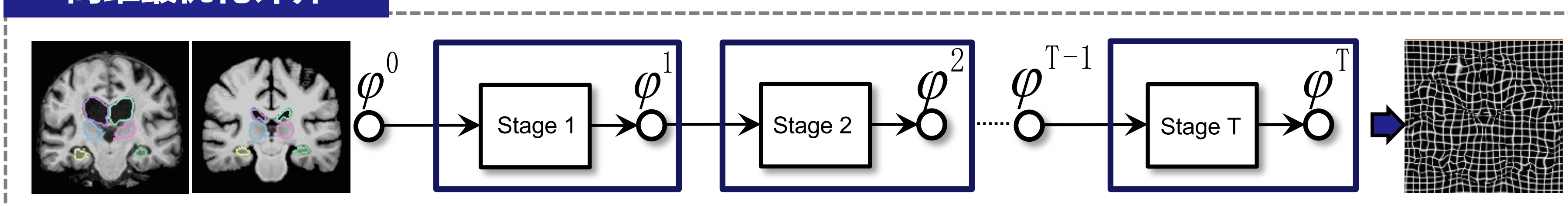
传统的基于 优化 方法

领域知识

嵌入

$$\min_{\varphi} \underbrace{E_D\left(\varphi; F, M(\varphi)\right)}_{\text{数据匹配项}} + \lambda \underbrace{E_R(\varphi)}_{\text{正则项}}$$

高维最优化计算



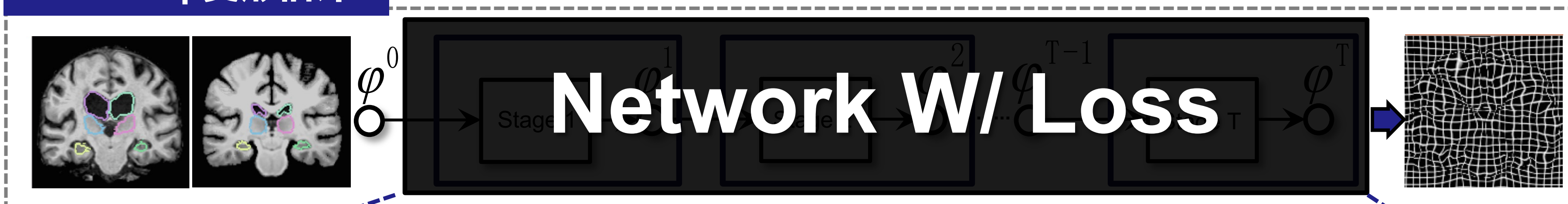
配准精度高

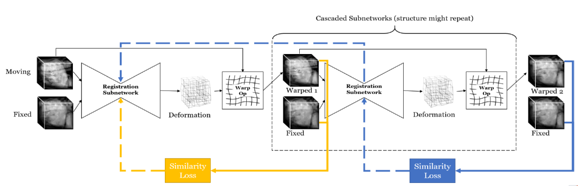
计算成本高

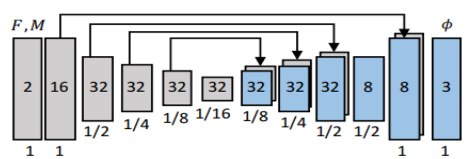
相关工作

■ 基于 深度学习 的方法

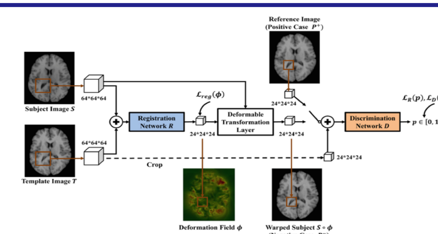
One-step变形估计







$$\mathcal{L} = \sum_{i,j} \|m_i \circ \phi_{ij} - f_{ij}\| + \lambda\,\mathrm{Reg}(\phi_{ij})$$



...

✔ 运行效率高

✘ 缺乏几何约束

相关工作

- 国际/国内优秀研究团队

Adrian Vasile Dalca
（麻省理工学院、哈佛医学院）

Mattias Heinrich
（吕贝克大学）

Ender Konukoglu
（苏黎世联邦理工学院）

Marc Niethammer
（北卡大学教堂山分校）

Tom Vercauteren
（伦敦国王学院）

Tony C.W. Mok
（香港科技大学）

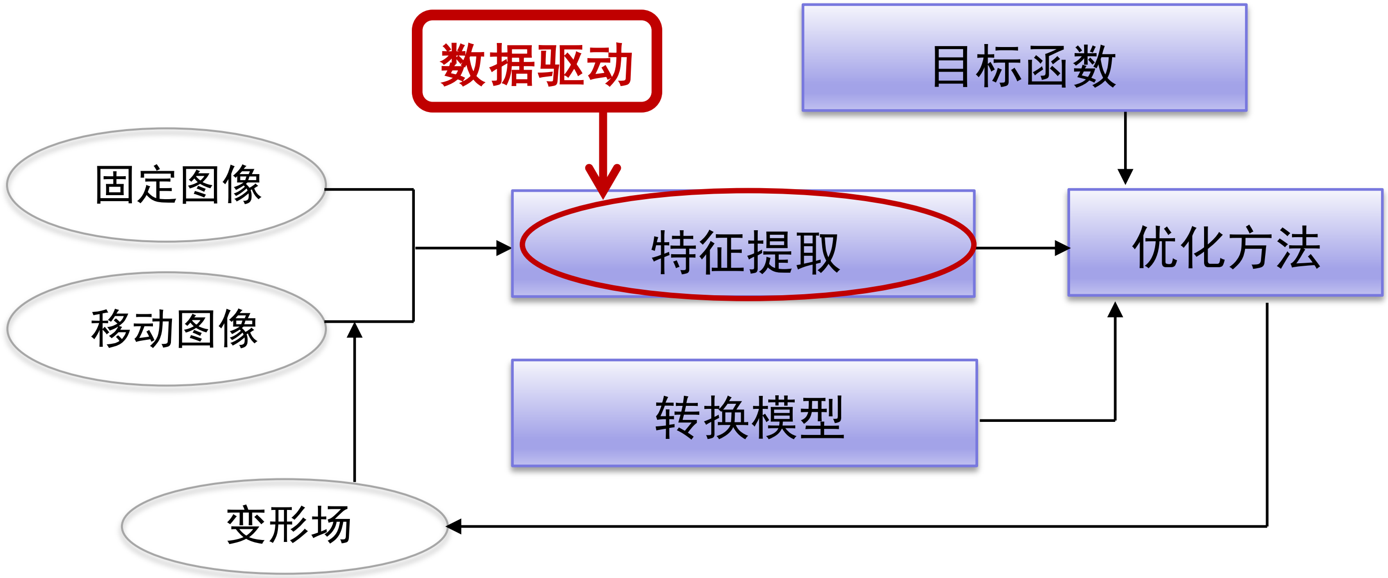
沈定刚 （上海科技大学）

第二章

基于双层特征学习的配准

Bilevel feature learning for image registration

研究动机

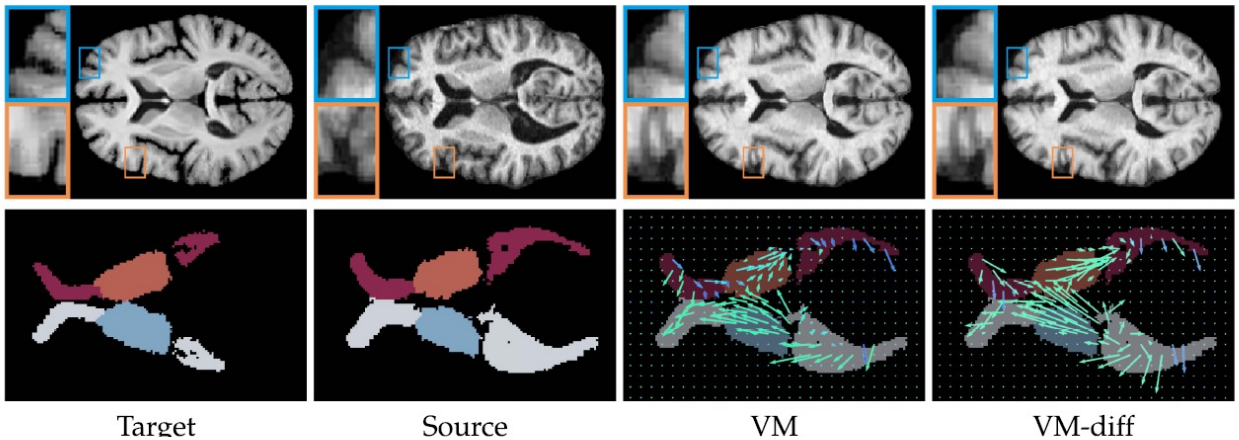


[1] Bi-level probabilistic feature learning for deformable image registration. ***IJCAI. 2020***: 723-730.

DAMO
ALIBABA DAMO ACADEMY

研究动机

主流Unet类配准网络的（不理想）对齐结果



◆ 大多数网络**难以自适应**执行**前端特征学习**阶段的配准信息

[1] Bi-level probabilistic feature learning for deformable image registration. ***IJCAI. 2020***: 723-730.

基于双层特征学习的配准

- **上层**：可变形配准优化； **下层**：特征学习（**约束**）

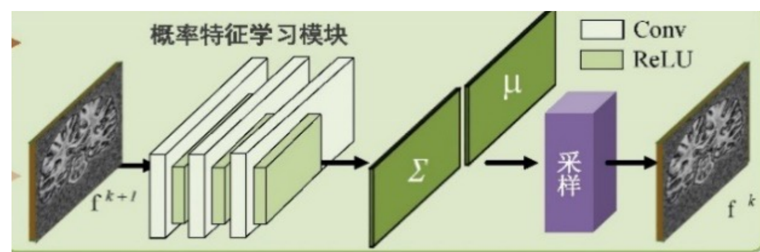
$$\min_{\varphi} E_D(\varphi; f_s, f_t) + E_R(\varphi),$$

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

- **概率特征学习** 模块

$$f = \arg\min_f \ln p\,(f|I, \varphi)$$

$$= \arg\min_f \underbrace{\ln p\,(I|f, \varphi)}_{\text{数据似然项}} + \underbrace{\ln p\,(f)}_{\text{先验}}$$



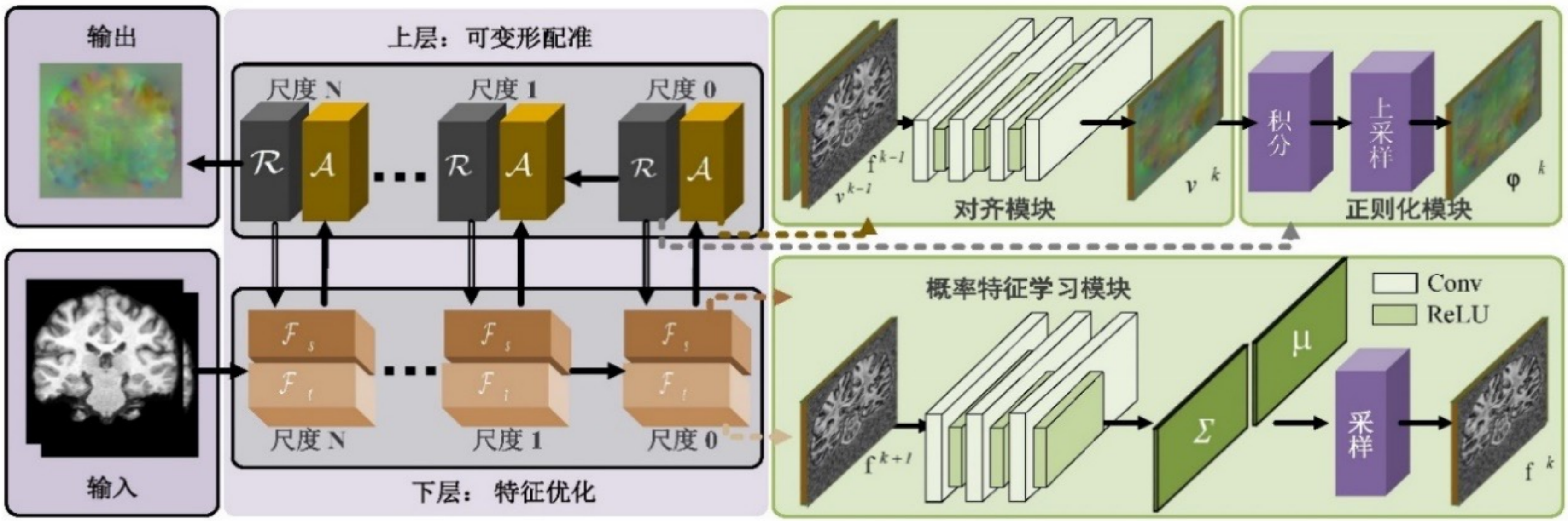
✓ **利用任务特定的配准信息**

✓ **利用特征的高斯先验**

[1] Bi-level probabilistic feature learning for deformable image registration. ***IJCAI. 2020***: 723-730.

基于双层特征学习的配准

- **流程图**（以 **端到端** 方式训练）



损失函数

特征域损失： $l_{KL}(\mu,\Sigma) = 1/2\big(tr(\Sigma) + ||\mu|| - log\, det(\Sigma) - m\big)$

图像域损失： $l(I_s, I_t; \varphi) = l_{NCC}(I_s \circ \varphi, I_t) + l_{smooth}(\varphi).$

[1] Bi-level probabilistic feature learning for deformable image registration. ***IJCAI. 2020***: 723-730.

基于双层特征学习的配准

- **准确度比较**

配准性能 **领先!**

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**

- **运行时间比较**

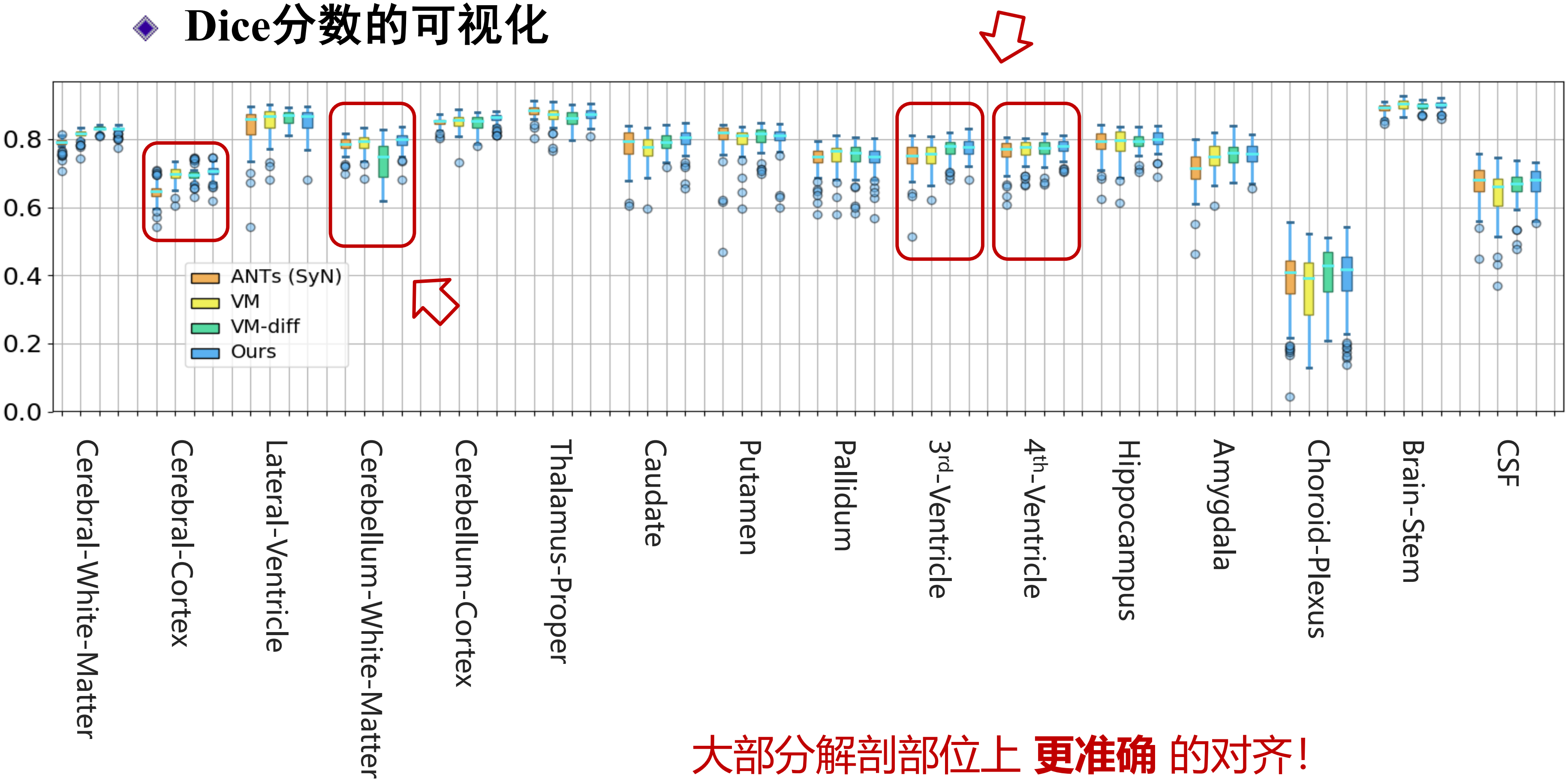
时间低于 **半秒!**

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. **IEEE TMI 2009.**
[2] Free-form deformation using lower-order B-spline for nonrigid image registration. **MICCAI 2014.**
[3] A reproducible evaluation of ants similarity metric performance in brain image registration. **Neuroimage 2011.**
[4] Voxelmorph: A learning framework for deformable medical image registration. **IEEE TMI 2019.**
[5] Unsupervised learning of probabilistic diffeomorphic registration for images and surfaces. **MedIA 2019.**

基于双层特征学习的配准

◆ **Dice分数的可视化**



大部分解剖部位上 **更准确** 的对齐！

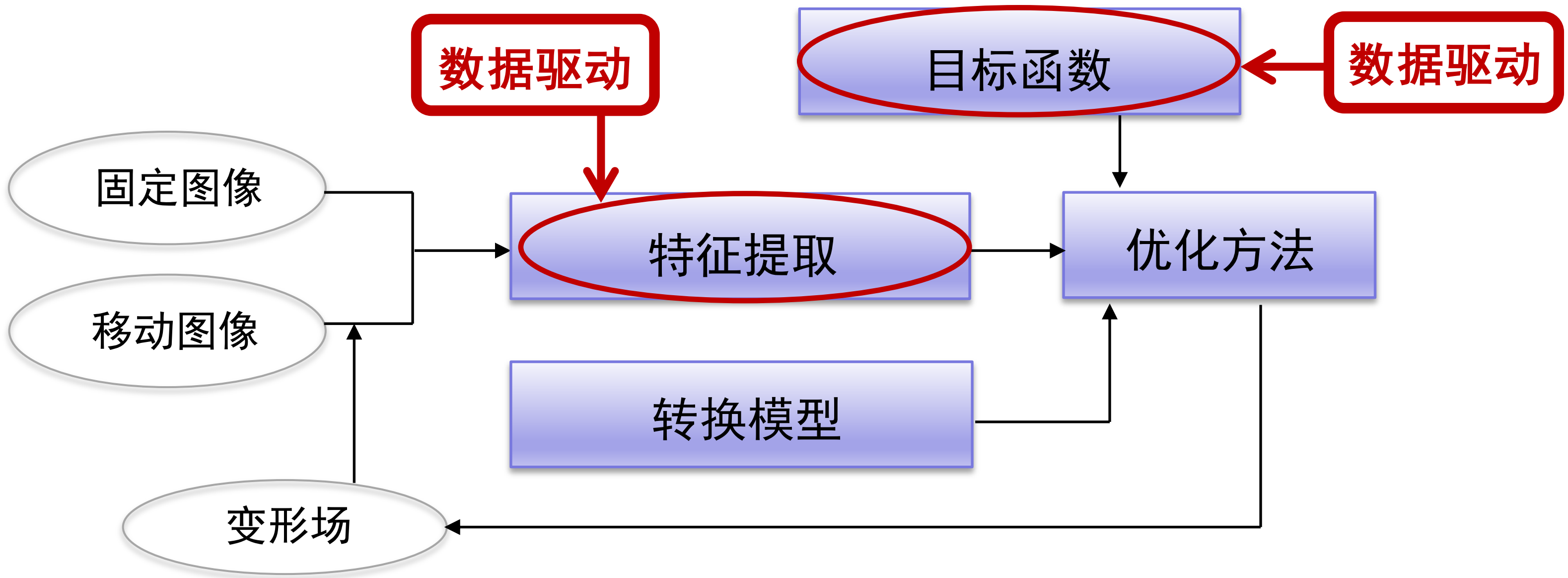
[1] Bi-level probabilistic feature learning for deformable image registration. ***IJCAI. 2020***: 723-730.

第三章

基于优化学习的可变形配准

Optimization learning for deformable image registration

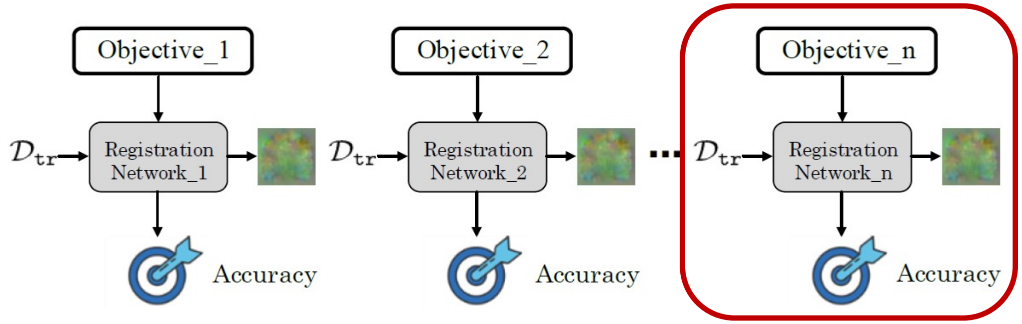
研究动机



[2] Learning deformable image registration from optimization: perspective, modules, bilevel training and beyond. ***IEEE TPAMI. 2021.***

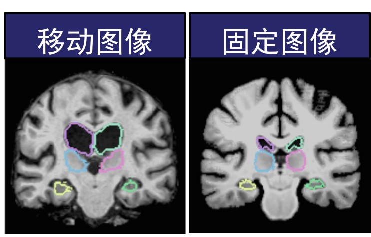
研究动机

常规的训练目标调整



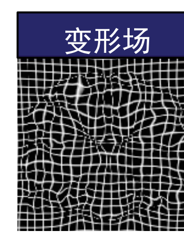
在单个GPU上运行一次需要**数小时到1-2天**

- 大多数配准网络训练目标**调试成本高**，且**缺乏物理约束**



✓ 具备物理约束

✓ 双层自调整训练



[2] Learning deformable image registration from optimization: perspective, modules, bilevel training and beyond. ***IEEE TPAMI. 2021.***

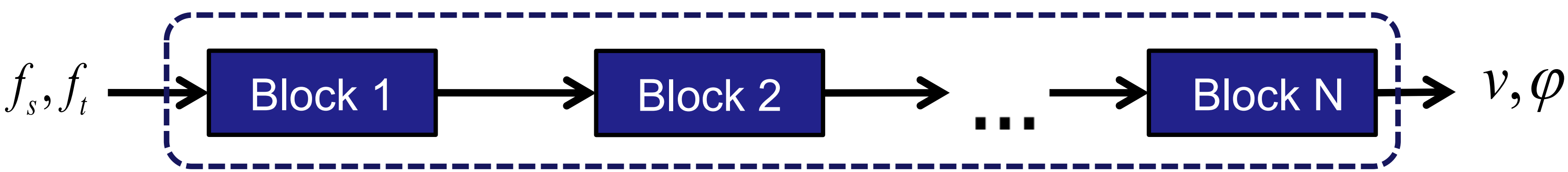
基于优化学习的可变形配准

- **微分同胚可变形** 配准的**基本**优化公式

$$\min_{v}\ \overbrace{Mat(\varphi\circ s,t)}^{\text{数据匹配}}+\lambda\overbrace{Reg(v)}^{\text{正则化}},$$

$$\underbrace{s.t.\ \frac{\partial\phi(t)}{\partial t}=v(\phi(t)),\ \phi(0)=Id,\ \varphi=\phi(1).}_{\text{微分同胚约束}}$$

- 基于**第二章特征空间**，进行 **深度传播**



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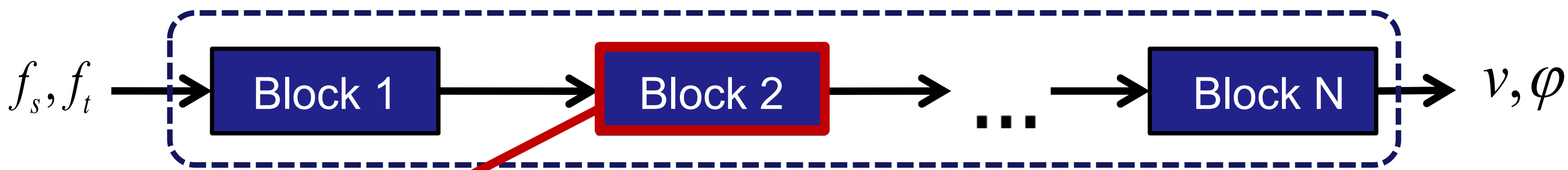
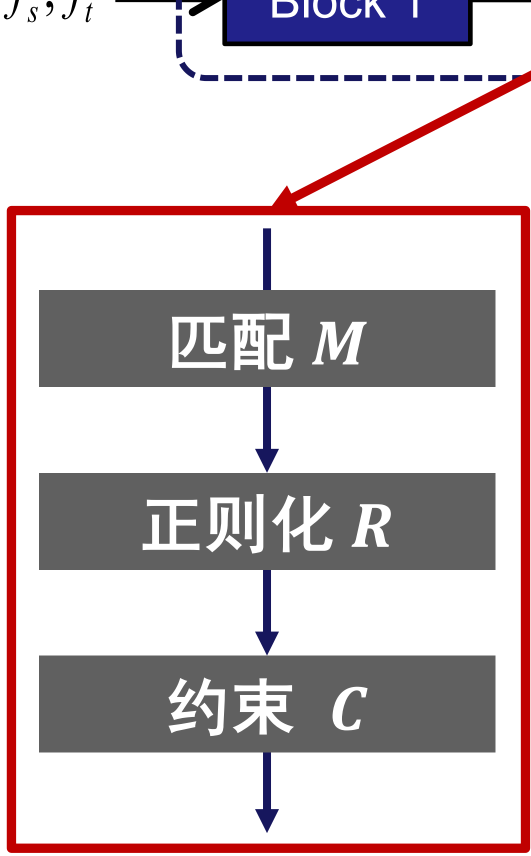
基于优化学习的可变形配准





- 基于误差映射的 **数据匹配** 模块

$$\boldsymbol{u}^{k+1} = \mathcal{M}\left(\boldsymbol{\varphi}^{k}, \boldsymbol{f}_{s}^{k+1}, \boldsymbol{f}_{t}^{k+1}, \boldsymbol{e}^{k+1}; \boldsymbol{w}_{\mathcal{M}^{k+1}}\right),$$

- 基于上下文的 **正则化** 模块

$$\boldsymbol{v}^{k+1} = \mathcal{R}\left(\boldsymbol{u}^{k+1}; \boldsymbol{w}_{\mathcal{R}^{k+1}}\right),$$

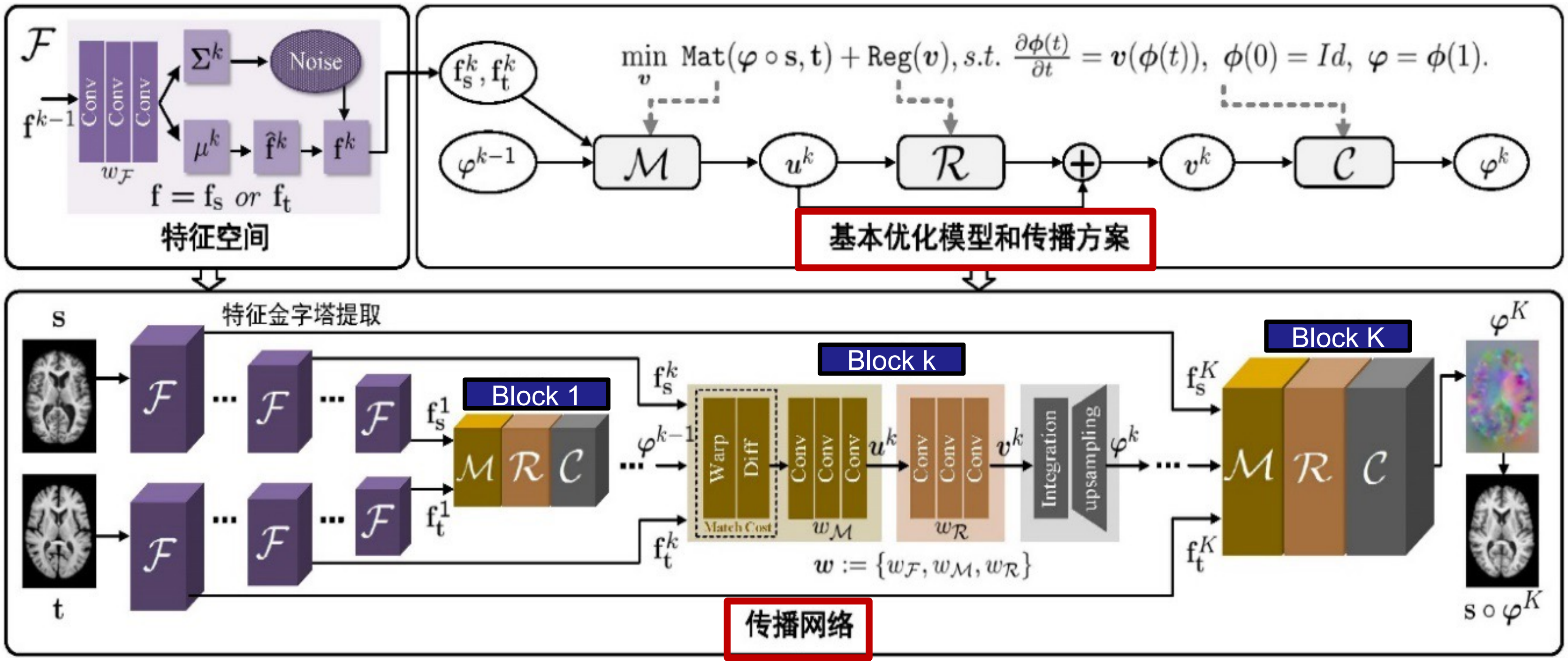
- 几何 **约束** 模块

$$\boldsymbol{\varphi}^{k+1} = \mathcal{C}\left(\boldsymbol{v}^{k+1}; \boldsymbol{w}_{\mathcal{C}}\right).$$

[2] Learning deformable image registration from optimization: perspective, modules, bilevel training and beyond. ***IEEE TPAMI. 2021.***

基于优化学习的可变形配准

- 基于**特征空间** 从 **优化** 中 **学习配准**



[2] Learning deformable image registration from optimization: perspective, modules, bilevel training and beyond. ***IEEE TPAMI. 2021.***

基于优化学习的可变形配准

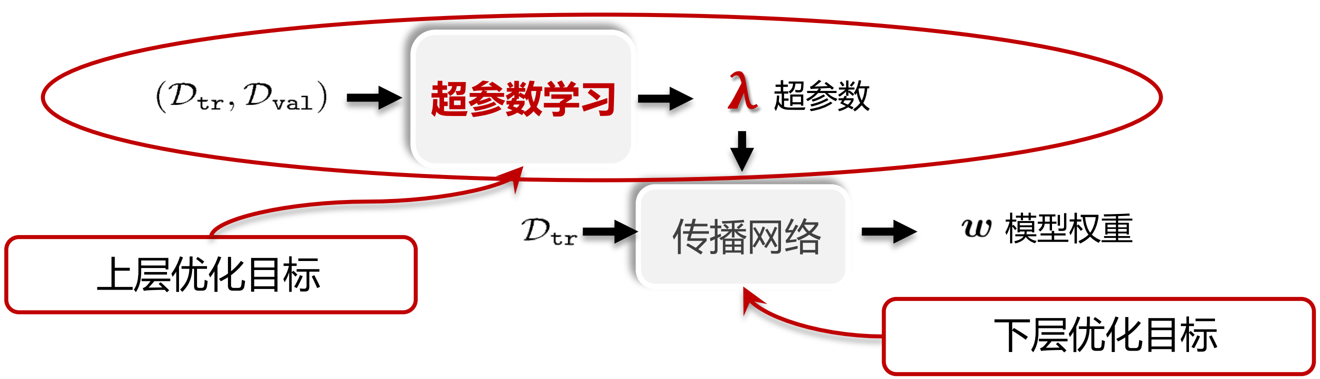
训练目标

$$l(\boldsymbol{w}(\boldsymbol{\lambda}),\boldsymbol{s}_i,\boldsymbol{t}_i)=\sum_{0}^{K}\lambda_{sta}^{k}\left(l_{KL}\left(\boldsymbol{\mu}^k,\boldsymbol{\Sigma}^k\right)+\lambda_{mat}l_{mat}\left(\boldsymbol{s}_i\circ\boldsymbol{\varphi}^k,\boldsymbol{t}_i\right)+\lambda_{reg}l_{reg}\left(\boldsymbol{v}^k\right)\right)$$

⇧

- **双层自调整训练**策略，**自动**学习 $\boldsymbol{\lambda}$

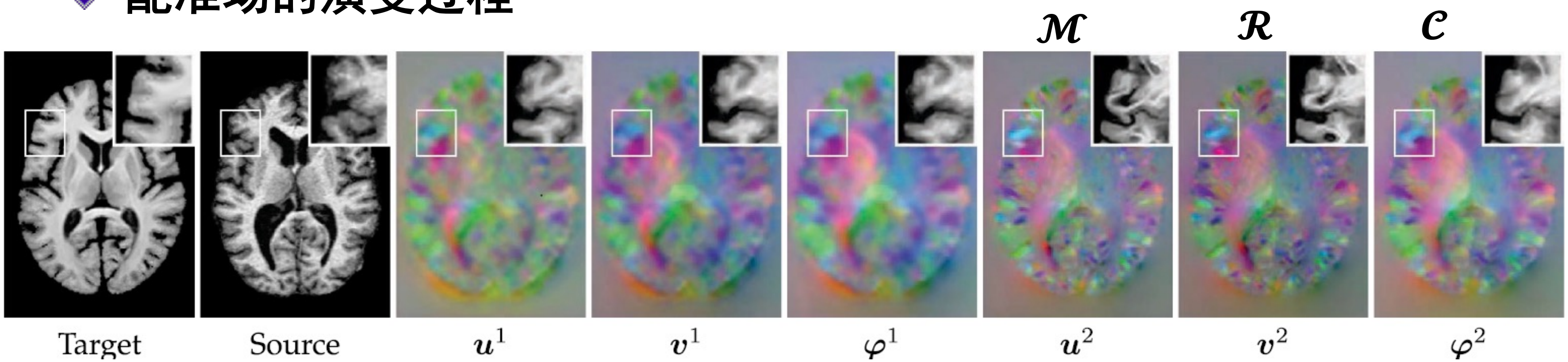
$$\min_{\boldsymbol{\lambda}}\ F(\boldsymbol{\lambda},\boldsymbol{w}),s.t.\boldsymbol{w}\in\mathcal{C}(\boldsymbol{\lambda})\ \text{ with } \mathcal{C}(\boldsymbol{\lambda}):=\left\{\arg\min_{\boldsymbol{w}}\ f(\boldsymbol{\lambda},\boldsymbol{w})\right\}$$



[2] Learning deformable image registration from optimization: perspective, modules, bilevel training and beyond. ***IEEE TPAMI. 2021.***

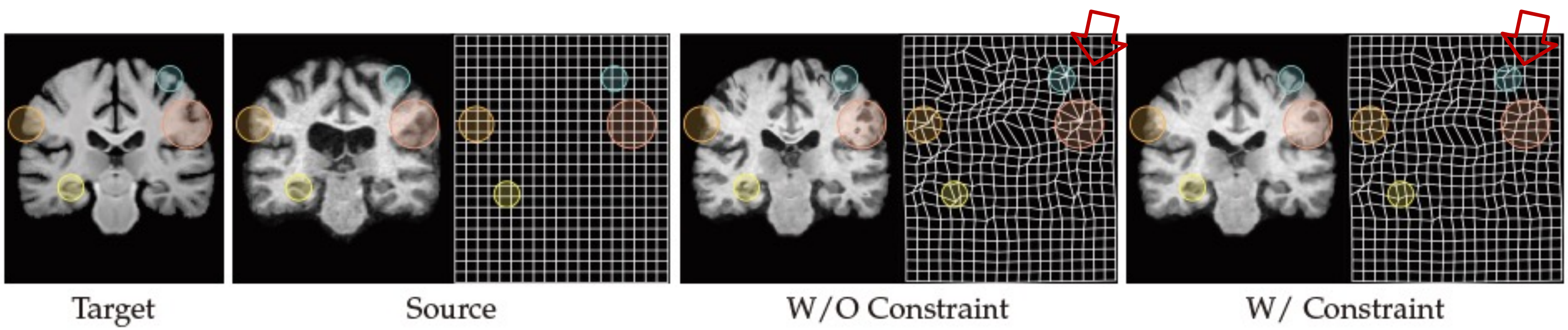
基于优化学习的可变形配准

◆ 配准场的演变过程



◆ 显式几何约束的消融分析

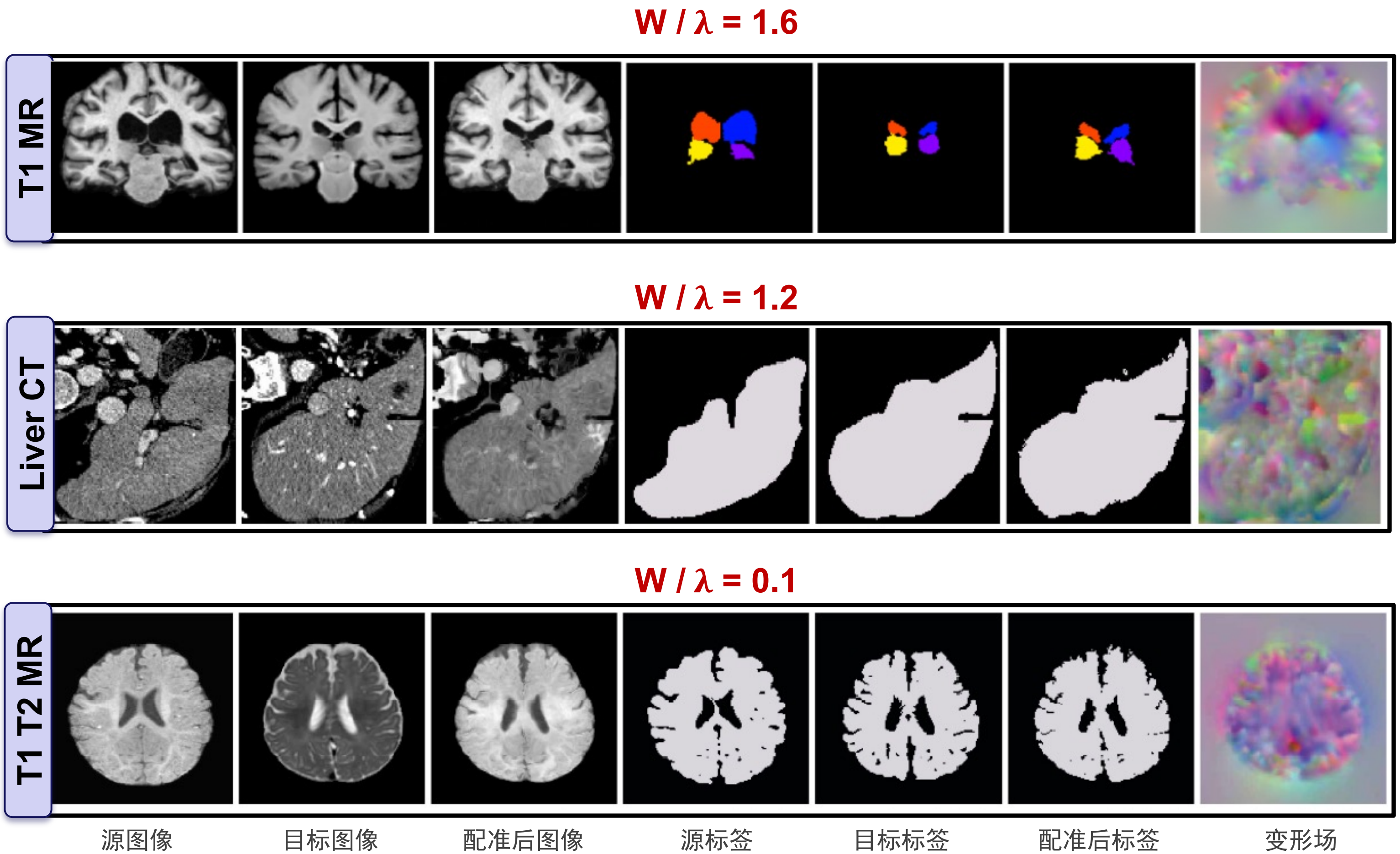
减少场的不合理 **折叠!**



[2] Learning deformable image registration from optimization: perspective, modules, bilevel training and beyond. ***IEEE TPAMI. 2021.***

基于优化学习的可变形配准

- 三个任务上自动学习到的超参数



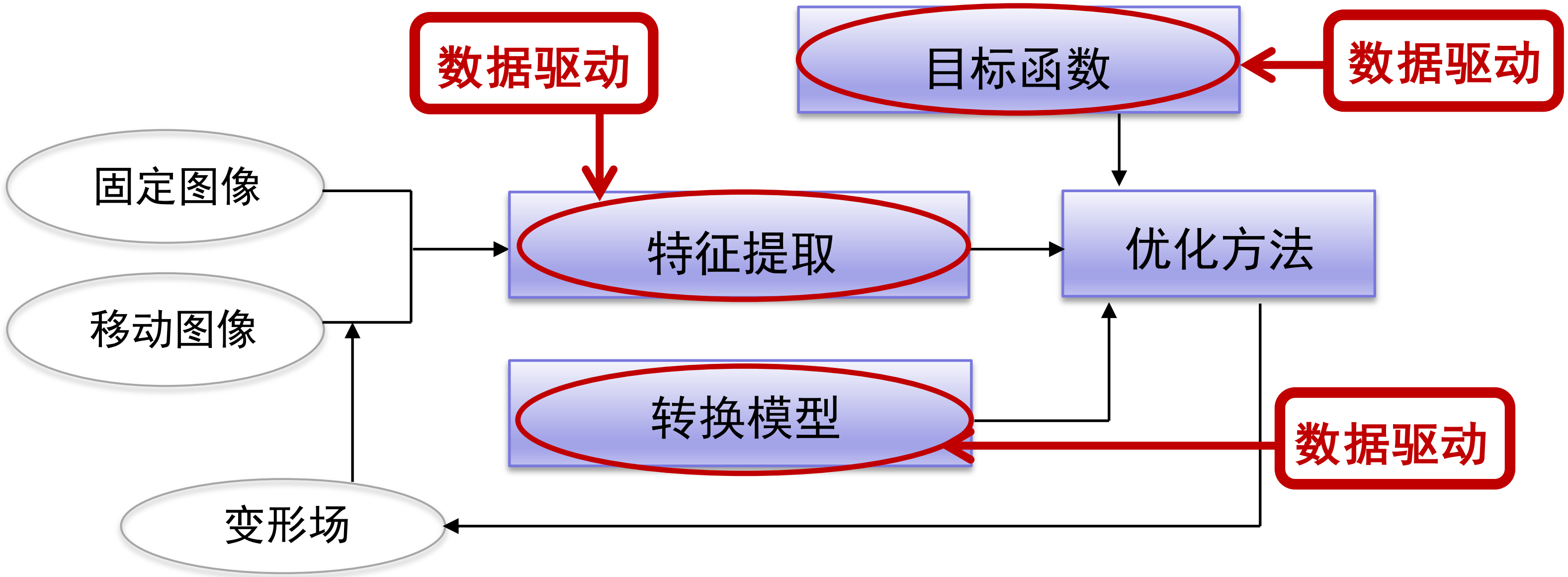
[2] Learning deformable image registration from optimization: perspective, modules, bilevel training and beyond. ***IEEE TPAMI. 2021.***

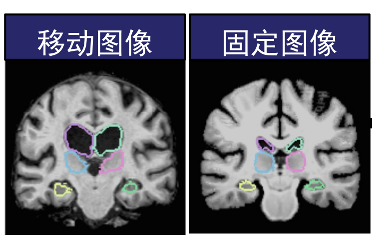
第四章

基于自动机器学习的配准

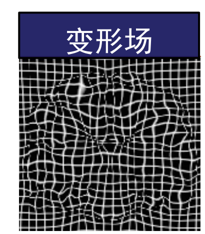
Automated learning for medical image registration

研究动机



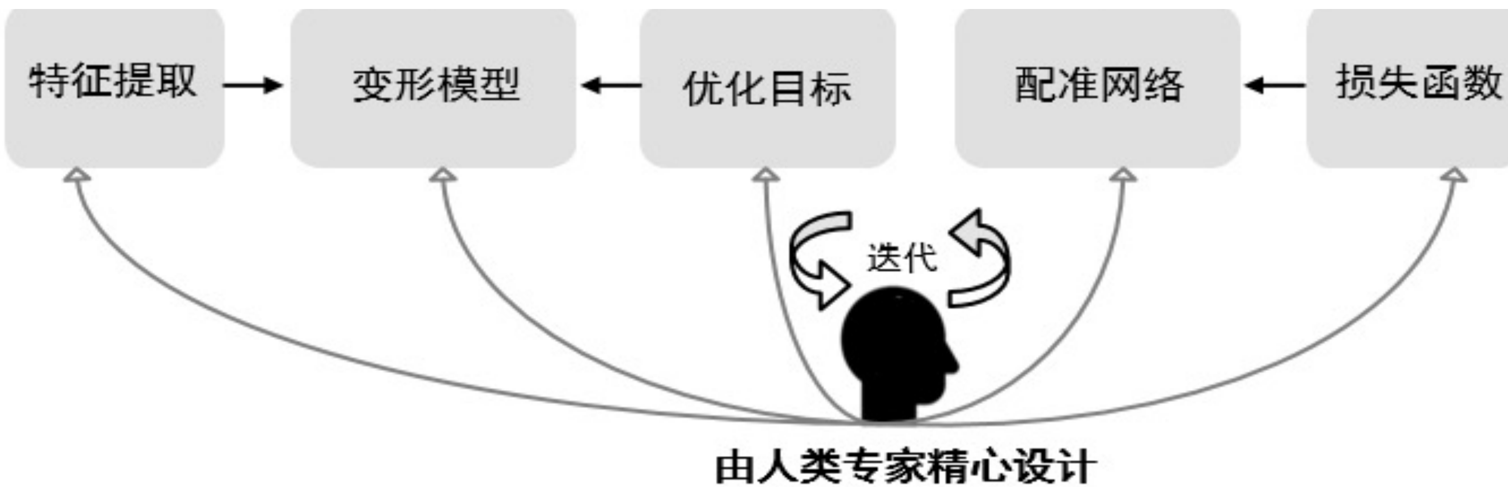


- ✓ 不依赖专业知识
- ✓ 降低验证成本

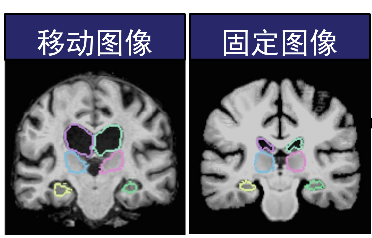


[3] Automated Learning for Deformable Medical Image Registration by Jointly Optimizing Network Architectures and Objective Functions.

研究动机

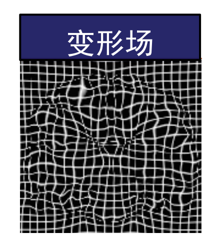


◆ 需要**计算机专家**付出**巨大努力**来**设计能量**或**调整网络架构**



✓ 不依赖专业知识

✓ 降低验证成本



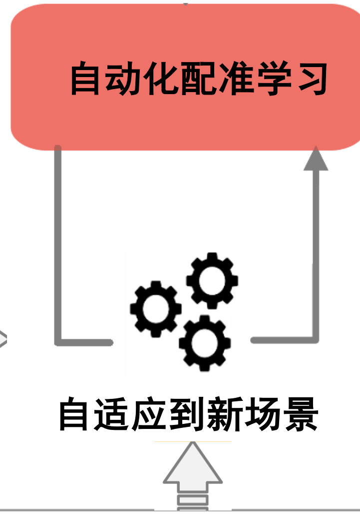
[3] Automated Learning for Deformable Medical Image Registration by Jointly Optimizing Network Architectures and Objective Functions.

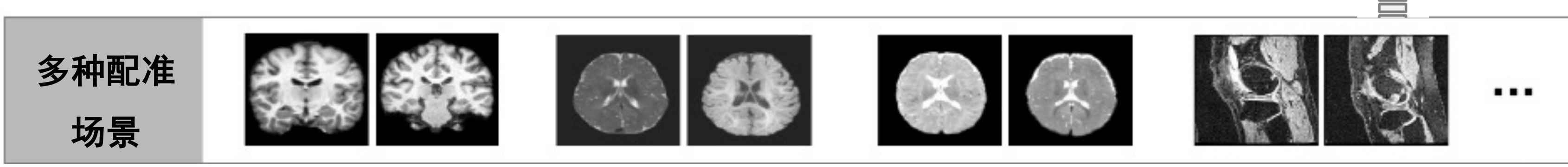
基于自动机器学习的配准

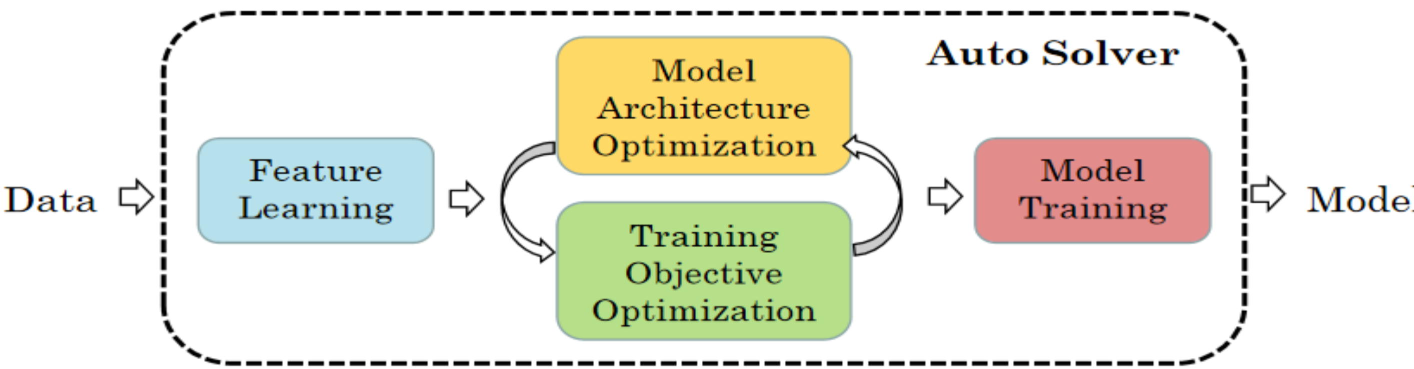
- **AutoReg** 的 **三层优化** 问题建模

$$
\min_{\lambda} \mathcal{L}_{val}^{seg}(\lambda, \alpha^*, \omega^*; s, t),
$$

$$
s.t. \begin{cases} \alpha^*(\lambda) = \arg\min_{\alpha} \mathcal{L}_{val}^{reg}(\alpha, \omega^*(\alpha); \lambda, s, t), \\ s.t.\ \omega^*(\alpha) = \arg\min_{\omega} \mathcal{L}_{tr}^{reg}(\omega; \alpha, \lambda, s, t). \end{cases}
$$





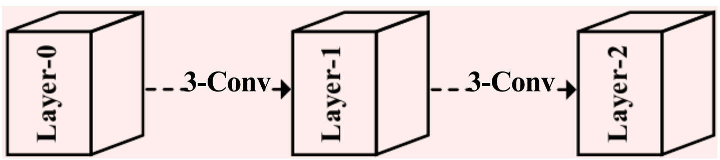


[3] Automated Learning for Deformable Medical Image Registration by Jointly Optimizing Network Architectures and Objective Functions.

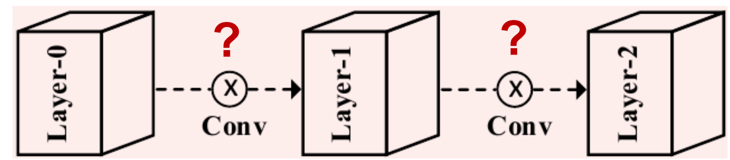
基于自动机器学习的配准

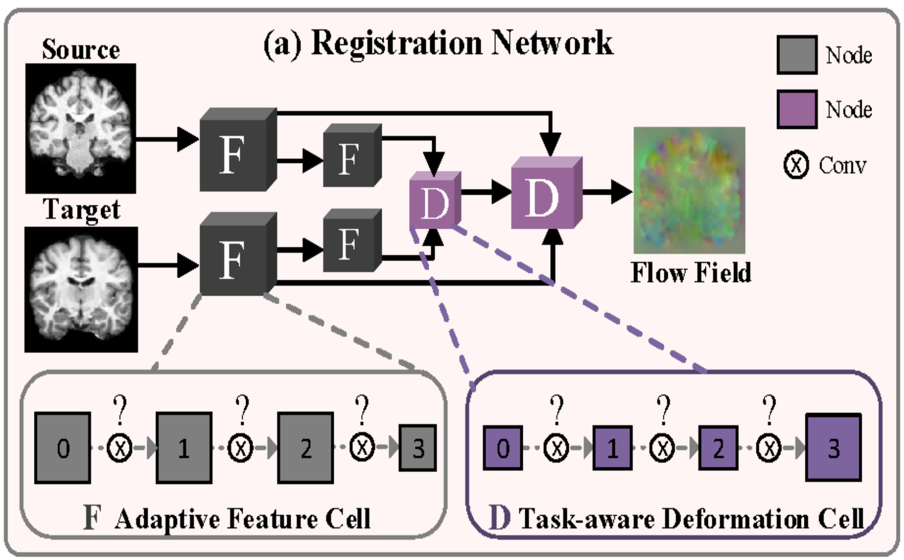
- **神经网络搜索：从手工设计到 自动搜索**

From



to





搜索空间

- 1×1×1 Conv (1-Conv)
- 3×3×3 Conv (3-Conv)
- 5×5×5 Conv (5-Conv)
- 3×3×3 Separable Conv (3-SConv)
- 5×5×5 Separable Conv (5-SConv)
- 3×3×3 Dilation Conv (3-DConv)
- 5×5×5 Dilation Conv (5-DConv)
- 7×7×7 Dilation Conv (7-DConv)

[3] Automated Learning for Deformable Medical Image Registration by Jointly Optimizing Network Architectures and Objective Functions.

基于自动机器学习的配准

◆ 结构最优性验证

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)**

◆ 计算成本

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

通常设置为 大于10

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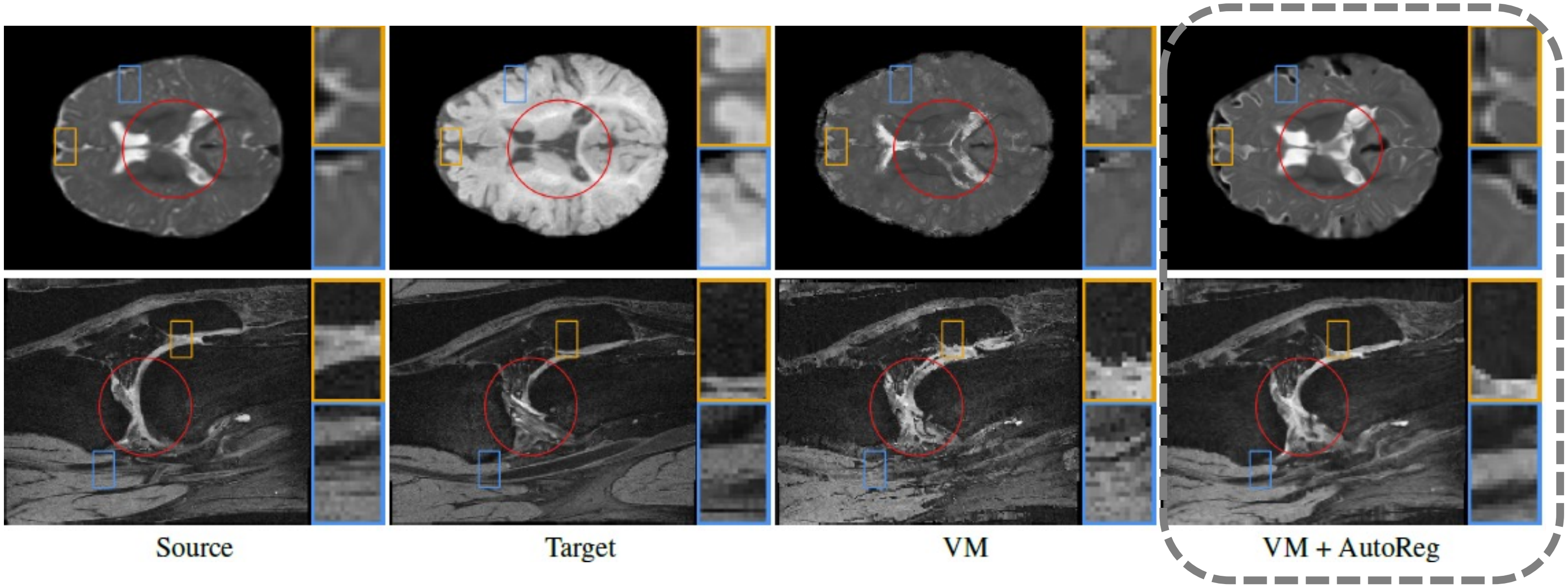
◆ 通用性分析

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)**



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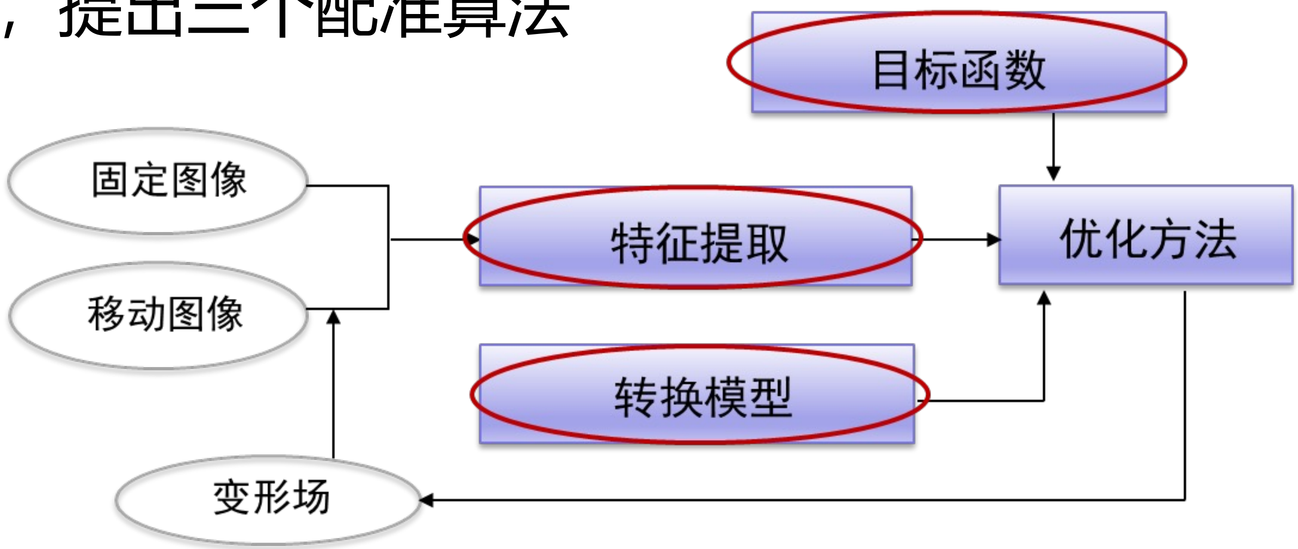
第五章

总结与展望

Summary and outlook

工作总结

- 将 **深度学习** 与 **双层优化** 相结合，从**配准框架**的三个方面出发，提出三个配准算法



- 基于双层特征学习的配准模型
- 新颖的相似度测量，双层自调整损失函数
- 自动优化特征/变形学习模块损失函数和网络结构的框架

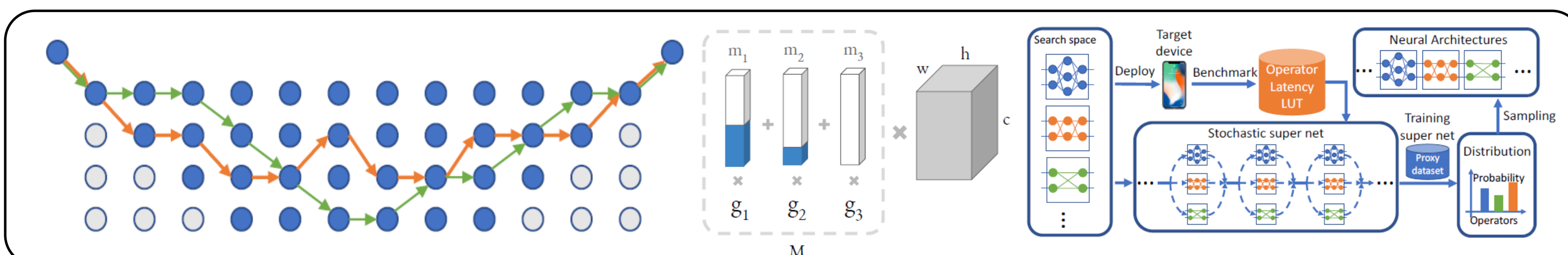
未来展望

□ 配准自动化学习

$$
\min_{\lambda}\ \mathcal{L}_{val}^{seg}(\lambda,\alpha^*,\omega^*;s,t),
$$

$$
s.t.\ \begin{cases} \boldsymbol{\alpha}^*(\lambda)=\arg\min_{\alpha}\ \mathcal{L}_{val}^{reg}(\alpha,\omega^*(\alpha);\lambda,s,t), \\ s.t.\ \boldsymbol{\omega}^*(\alpha)=\arg\min_{\omega}\ \mathcal{L}_{tr}^{reg}(\omega;\alpha,\lambda,s,t). \end{cases}
$$

- **涵盖其他结构超参数**
  - 控制单元之间连接的网络拓扑
  - 层数和分辨率级别，…



DAMO
ALIBABA DAMO ACADEMY

感谢团队培养

谢谢聆听 请批评指正