文献分享1
LT-Net: Label Transfer by Learning Reversible Voxel-Wise Correspondence for One-Shot Medical Image Segmentation

贺珂

Motivation

- Voxelmorph系列, 监督信号有限. 尽可能的利用图像自带的信息进行监督.
- 文章的主题: 一致性, 分为两种
  forward-backward consistency😊
  cycle-consistency
- 解释一下标题:
  label transfer: atlas配准中利用atlas的标签经过变形得到其他图像标签
  One-shot segmentation: atlas-based segmentation 只需要一个label
  reversible Voxel-wise correspondence: 变刑场逆变换的一致性

Overview

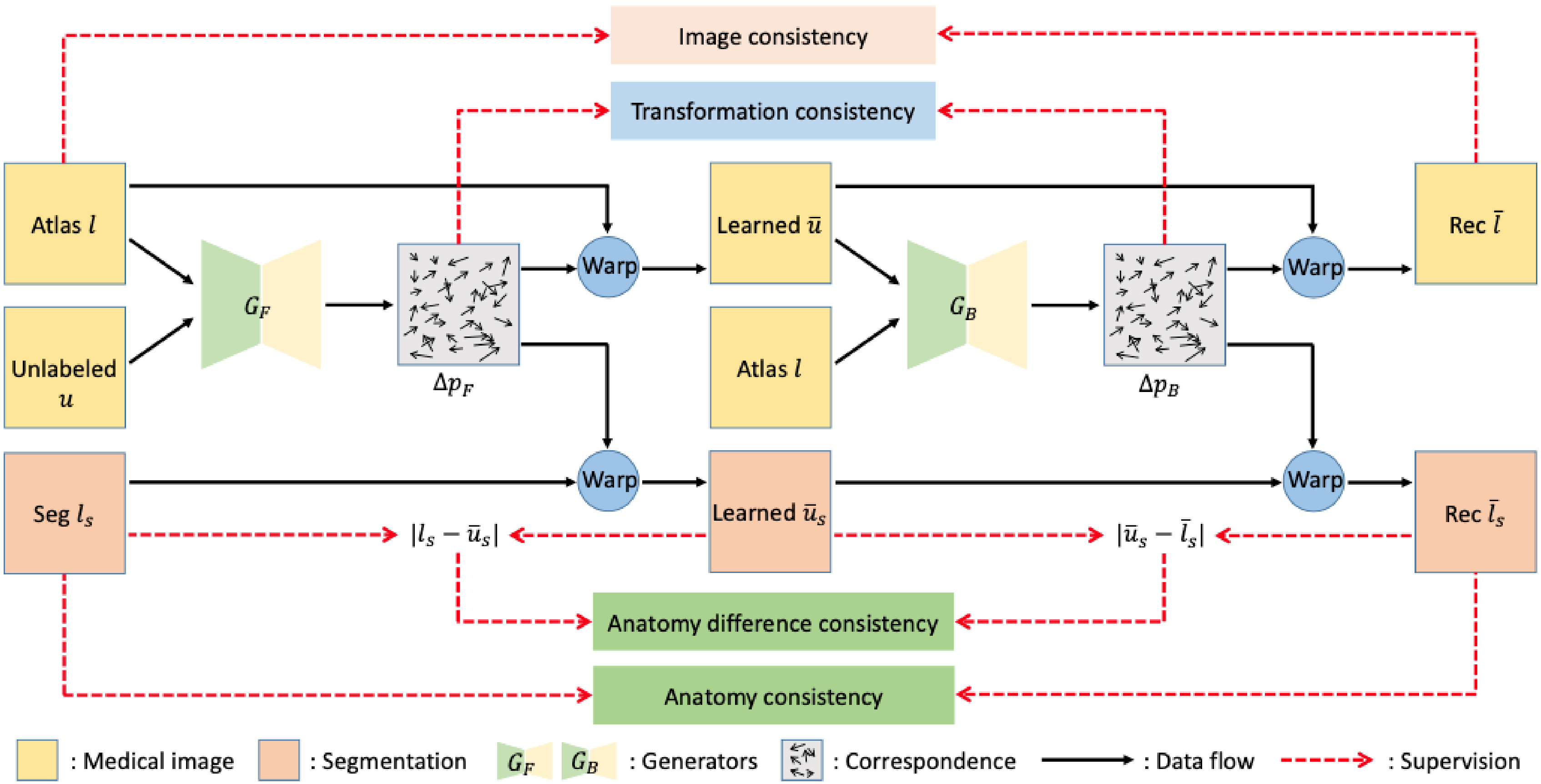
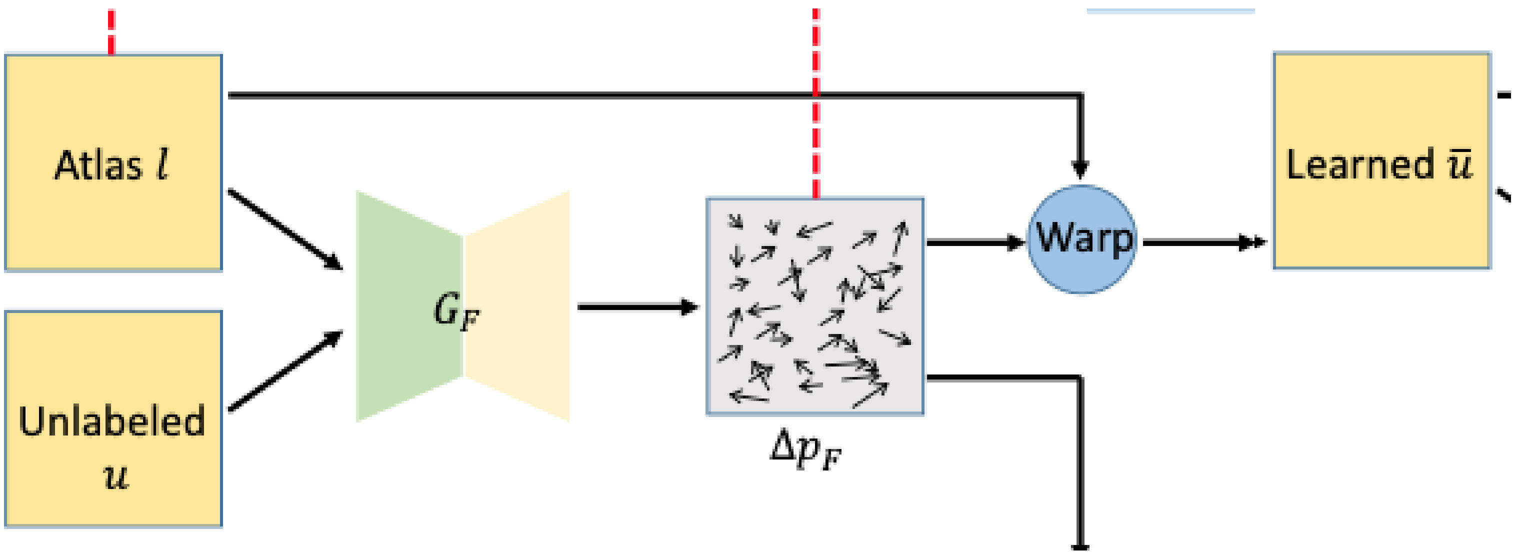


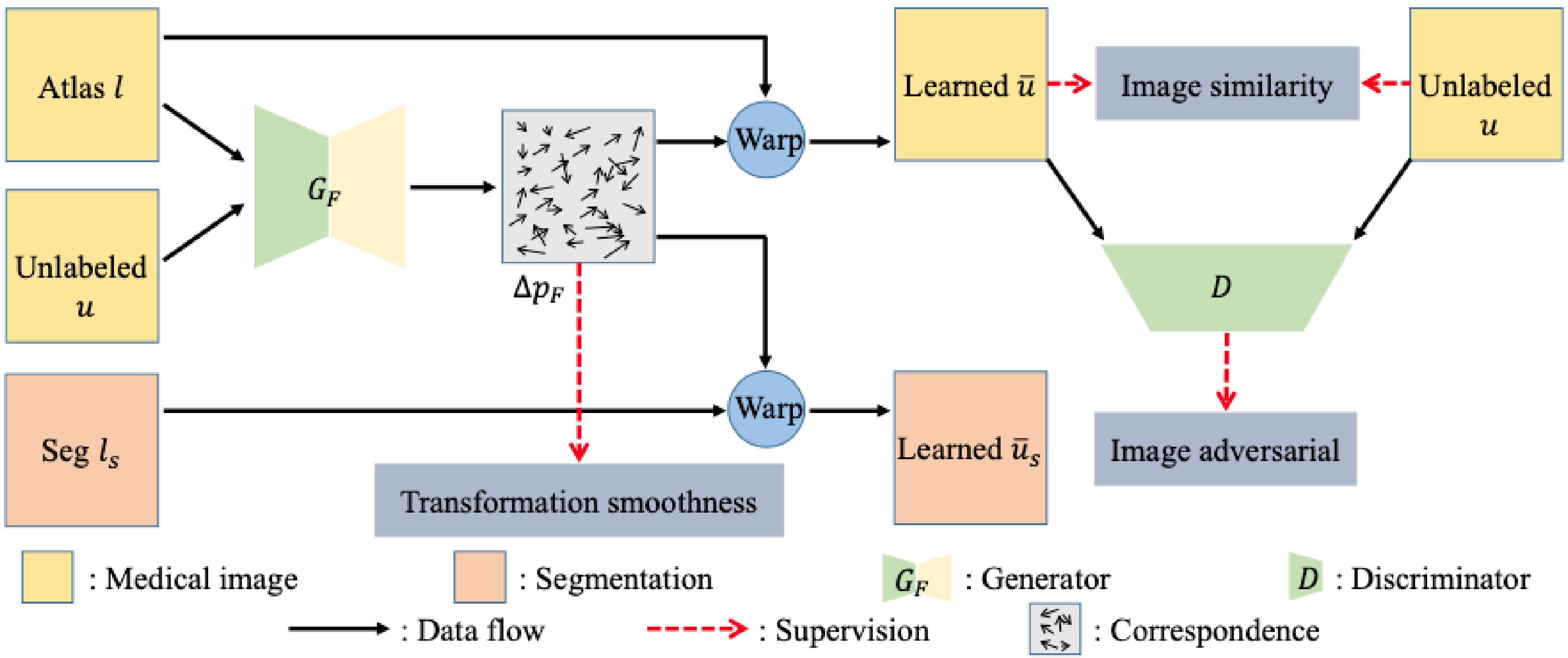
Image consistency
Transformation consistency
Atlas l
Unlabeled u
G_F
Δp_F
Warp
Learned $\bar{u}$
Atlas l
G_B
Δp_B
Warp
Rec $\bar{l}$
Seg l_s
Warp
Learned $\bar{u}_s$
Warp
Rec $\bar{l}_s$
$|l_s - \bar{u}_s|$
$|\bar{u}_s - \bar{l}_s|$
Anatomy difference consistency
Anatomy consistency
: Medical image
: Segmentation
G_F G_B : Generators
: Correspondence
: Data flow
: Supervision

Explanation 1

- Voxelmorph

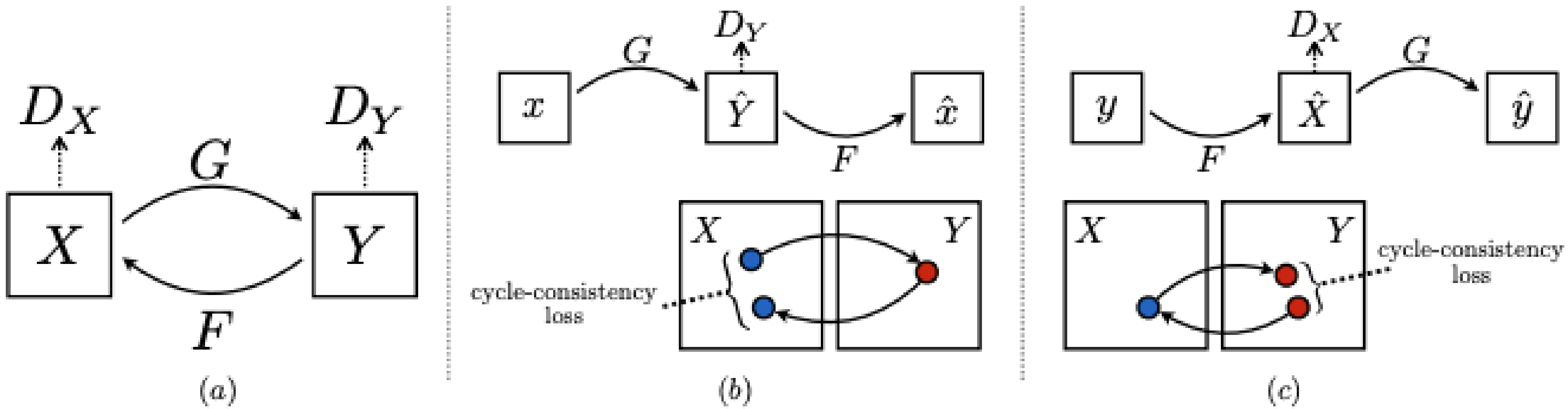


Explanation 2



Explanation 3

- CycleGAN



如何理解本文的两个网络以及cycle-loss:

用cyclegan框架看看

Loss function

$$\mathcal{L} = \mathcal{L}_{\mathrm{GAN}} + \mathcal{L}_{\mathrm{sim}} + \lambda_1 \mathcal{L}_{\mathrm{cyc}} + \lambda_2 (\mathcal{L}_{\mathrm{anatomy\_cyc}} + \mathcal{L}_{\mathrm{smooth}} + \mathcal{L}_{\mathrm{trans}} + \mathcal{L}_{\mathrm{diff\_cyc}}),$$

L_{gan}: 本文中的voxelmorph是用了GAN loss作为监督的:

$$\mathcal{L}_{\mathrm{GAN}}(l, u, \bar{u}) = \mathbb{E}_{u \sim p_d(u)}[\|D(u)\|_2] + \mathbb{E}_{l \sim p_d(l), u \sim p_d(u)}[\|D(\bar{u}) - \mathbf{1}\|_2],$$

$L_{similarity} + L_{smooth}$: 原始voxelmorph的loss

Cycle Loss

$$\mathcal{L}_{\text{cyc}}(l, \bar{l}) = \mathbb{E}_{l \sim p_d(l)}[\|\bar{l} - l\|_1].$$

$$\mathcal{L}_{\text{anatomy\_cyc}}(l_s, \bar{l}_s) = 1 - \frac{2 \sum_{t \in \Omega} l_s(t) \bar{l}_s(t)}{\sum_{t \in \Omega} l_s^2(t) + \sum_{t \in \Omega} \bar{l}_s^2(t)}.$$

$$\mathcal{L}_{\text{diff\_cyc}}(l_s, \bar{u}_s, \bar{l}_s) = \sum_{t \in \Omega} \rho(|l_s(t) - \bar{u}_s(t)| - |\bar{u}_s(t) - \bar{l}_s(t)|).$$

Forward-backward loss

$$\mathcal{L}_{\text{trans}}(\Delta p_F, \Delta p_B) = \sum_{t \in \Omega} \rho(\Delta p_F(t) + \Delta p_B(t + \Delta p_F(t))),$$

../../seminar/2020-3-10.pptx

Ablation Study

	Mean (std)	Min	Max
VoxelMorph	76.0 (9.7)	61.7	80.1
$+ \mathcal{L}_{\mathrm{GAN}}$	79.0 (3.1)	72.7	81.9
$+ \mathcal{L}_{\mathrm{GAN}} + \mathcal{L}_{\mathrm{cyc}}$	**79.2 (2.8)**	72.7	82.1

	Mean (std)	Min	Max
Baseline	79.2 (2.8)	72.7	82.1
$+ \mathcal{L}_{\mathrm{trans}}$	80.9 (2.7)	73.6	83.2
$+ \mathcal{L}_{\mathrm{anatomy\_cyc}}$	80.5 (2.5)	74.2	83.1
$+ \mathcal{L}_{\mathrm{trans}} + \mathcal{L}_{\mathrm{anatomy\_cyc}}$	81.4 (2.6)	74.4	83.8
$+\mathcal{L}_{\mathrm{trans}} + \mathcal{L}_{\mathrm{anatomy\_cyc}} + \mathcal{L}_{\mathrm{diff\_cyc}}$	**82.3 (2.5)**	75.6	84.2

Comparison to other methods

	Mean (std)	Min	Max
VoxelMorph	76.0 (9.7)	61.7	80.1
DataAug	80.4 (4.3)	73.8	84.0
LT-Net	82.3 (2.5)	75.6	84.2
U-Net (upper bound)	86.5 (6.3)	83.7	89.2

Fast Symmetric Diffeomorphic Image Registration with Convolutional Neural Networks

Diffeomorphic registration

- 微分同胚变刑场
  之前出现在: 2018年的这篇论文
  Unsupervised Learning for Fast Probabilistic Diffeomorphic Registration

- ordinary differential equation (ODE)

$$\frac{\partial \phi^{(t)}}{\partial t} = \boldsymbol{v}(\phi^{(t)})$$

- 非常非常关键的假设: v 是一个静止速度场(stationary velocity field)

Method	Avg. Dice	GPU sec	CPU sec	$\lvert J_\Phi \rvert \leq 0$	Uncertainty
Affine only	0.567 (0.157)	0	0	0	No
ANTs (SyN)	0.750 (0.135)	-	9059 (2023)	6505 (3024)	No
VoxelMorph	0.750 (0.137)	0.554 (0.017)	144 (1)	18096 (4230)	No
Ours	**0.753** (0.137)	**0.451** (0.011)	**51** (0.2)	**0.7** (2.0)	**Yes**

Diffeomorphic registration

- 初始条件

$$\phi^{(1/2^T)} = x + v(x)/2^T$$

$$\phi^{(1/2^{t-1})} = \phi^{(1/2^t)} \circ \phi^{(1/2^t)}$$

- 对称性假设(这是voxelmorph v2没有的假设):

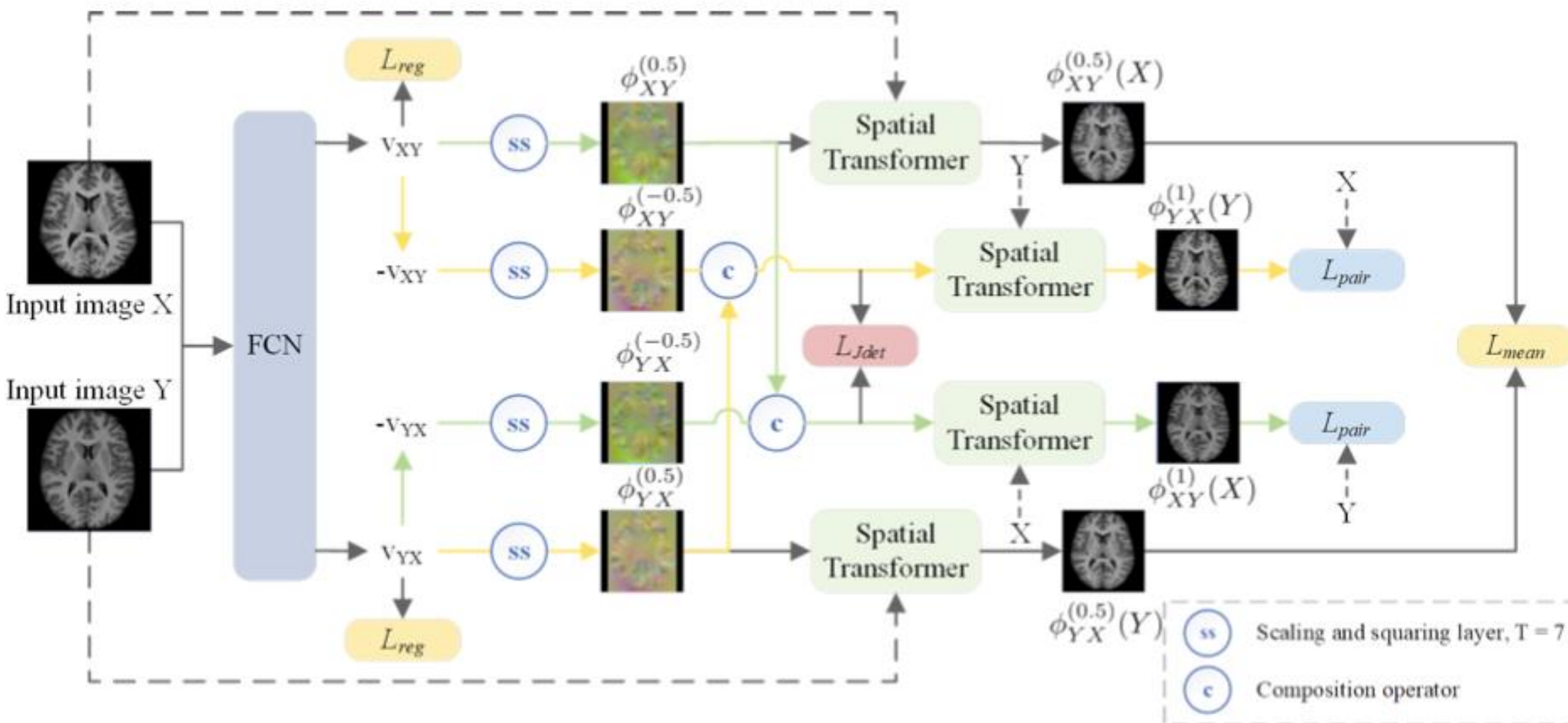
ods [31, 3, 23], we propose to learn the two separated time 0.5 deformation fields that warp both X and Y to their mean shape M in the geodesic path. After the model converges,

Diffeomorphic registration

- 由上一个假设可以得到

$$\phi_{XY}^{(1)} = \phi_{YX}^{(-0.5)}(\phi_{XY}^{(0.5)}(x)),$$

Overview



Input image X
Input image Y
FCN
v_{XY}
$-v_{XY}$
$-v_{YX}$
v_{YX}
L_{reg}
L_{reg}
ss
c
$\phi_{XY}^{(0.5)}$
$\phi_{XY}^{(-0.5)}$
$\phi_{YX}^{(-0.5)}$
$\phi_{YX}^{(0.5)}$
Spatial Transformer
Spatial Transformer
Spatial Transformer
Spatial Transformer
L_{Jdet}
$\phi_{XY}^{(0.5)}(X)$
$\phi_{YX}^{(1)}(Y)$
$\phi_{XY}^{(1)}(X)$
$\phi_{YX}^{(0.5)}(Y)$
X
Y
L_{pair}
L_{pair}
L_{mean}
Scaling and squaring layer, T = 7
Composition operator

Smooth loss function

$$J_\phi(p) = \begin{pmatrix} \frac{\partial \phi_x(p)}{\partial x} & \frac{\partial \phi_x(p)}{\partial y} & \frac{\partial \phi_x(p)}{\partial z} \\ \frac{\partial \phi_y(p)}{\partial x} & \frac{\partial \phi_y(p)}{\partial y} & \frac{\partial \phi_y(p)}{\partial z} \\ \frac{\partial \phi_z(p)}{\partial x} & \frac{\partial \phi_z(p)}{\partial y} & \frac{\partial \phi_z(p)}{\partial z} \end{pmatrix}$$

$$\mathcal{L}_{Jdet} = \frac{1}{N} \sum_{p \in \Omega} \sigma(-|J_\phi(p)|)$$