GraphRegNet: Deep Graph Regularisation Networks on Sparse Keypoints for Dense Registration of 3D Lung CTs

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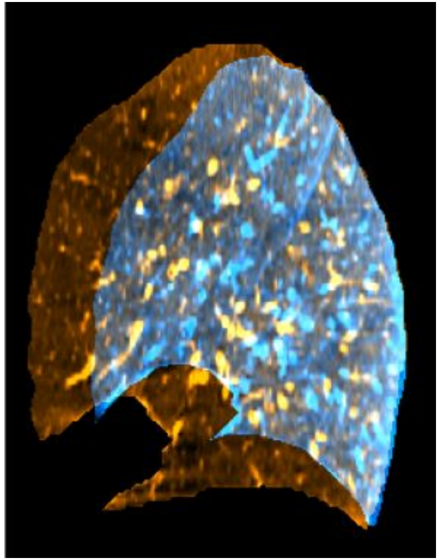
Motivation



Knowing airflow in the lung helps diagnose disease such as COPD (Chronic Obstructive Pulmonary Disease), Asthma, lung cancer

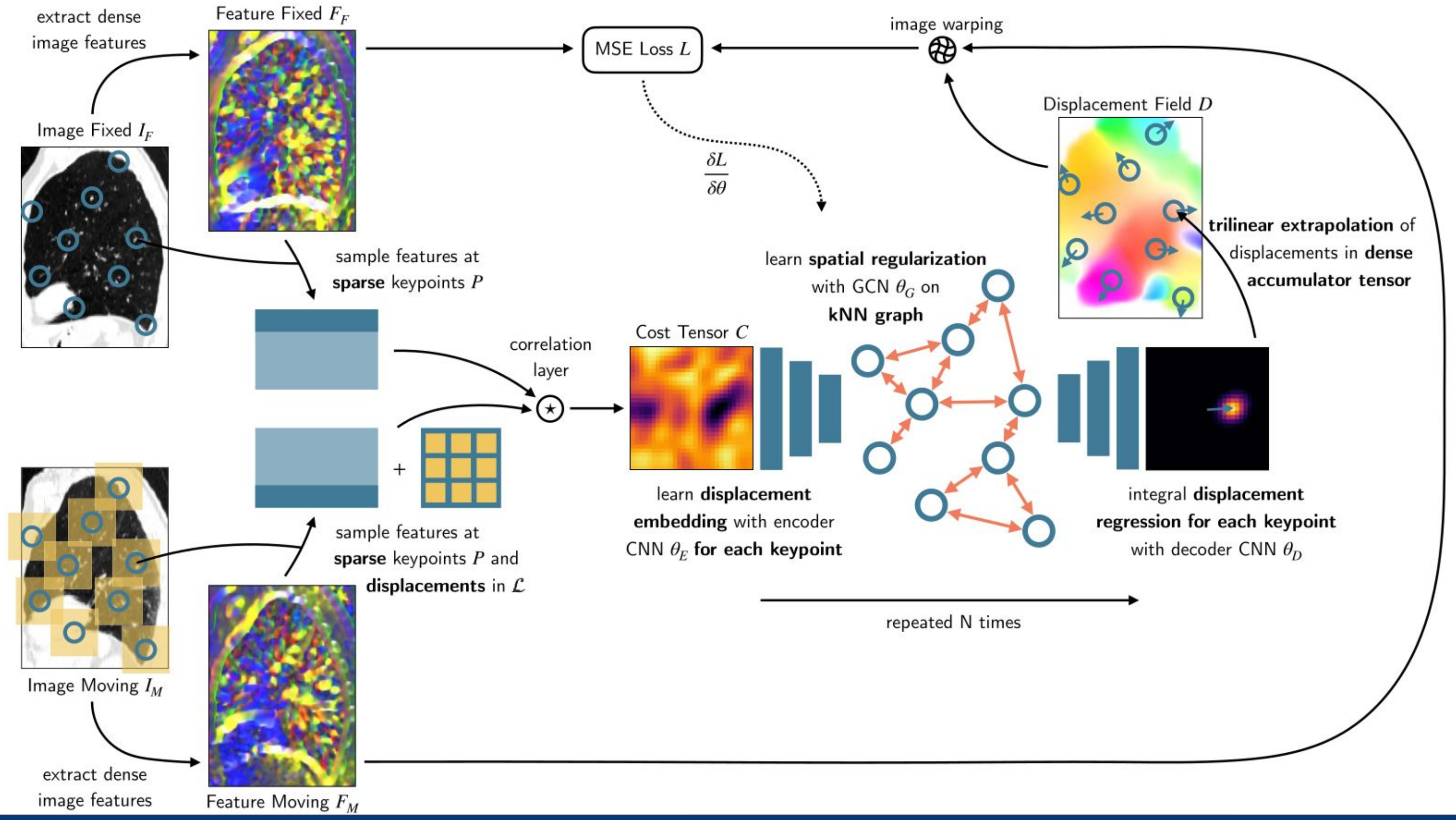
Current DL method doesn’t reach an acceptable accuracy

Challenge :

Large motion estimation of the lung between inhale and exhale

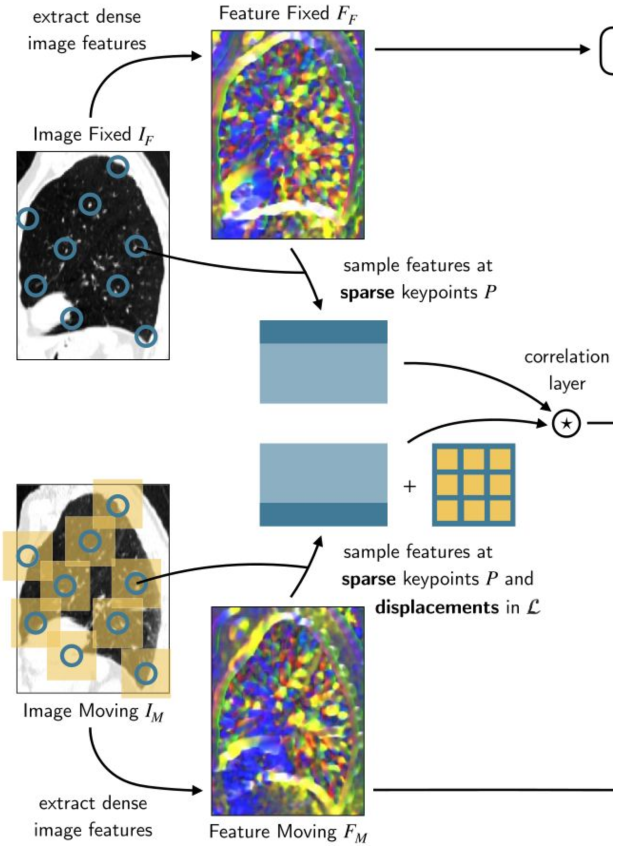
Presents a lightweight U - Net like architecture to predict large deformation displacement field that allows inhale to exhale CT scan registration

Method



extract dense image features
Feature Fixed F_F
MSE Loss L
image warping
Image Fixed I_F
Displacement Field D
$\frac{\delta L}{\delta \theta}$
trilinear extrapolation of displacements in dense accumulator tensor
sample features at sparse keypoints P
learn spatial regularization with GCN θ_G on kNN graph
correlation layer
Cost Tensor C
+
learn displacement embedding with encoder CNN θ_E for each keypoint
integral displacement regression for each keypoint with decoder CNN θ_D
sample features at sparse keypoints P and displacements in $\mathcal{L}$
repeated N times
Image Moving I_M
extract dense image features
Feature Moving F_M

Preprocessing



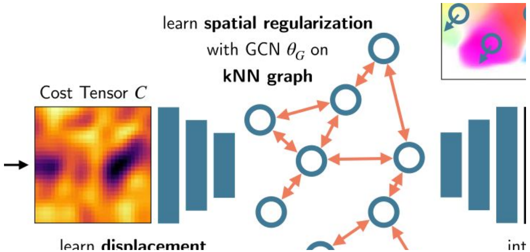
Fixed Image (Inhale), Moving Image (Exhale)

1. Preprocess the image
2. **Sparse** Keypoint extraction using Foerstner interest operator + max pooling
3. Feature extraction using MIND (Modality Independent Neighbourhood Descriptor)
4. Cost tensor generation using the extracted features

p : keypoints , l : displacement locations

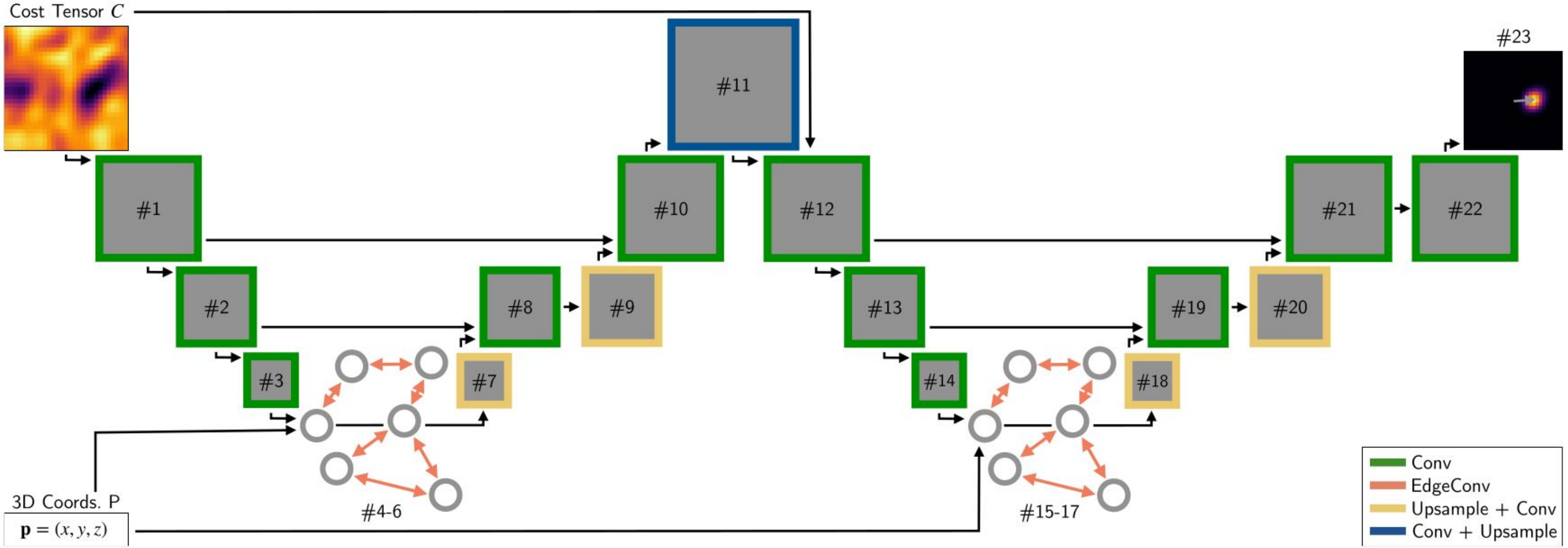
$$C(\mathbf{p}, \mathbf{l}) = \frac{1}{12} \sum_{i=0}^{11} (F_F^i(\mathbf{p}) - F_M^i(\mathbf{p} + \mathbf{l}))^2$$

GraphRegNet

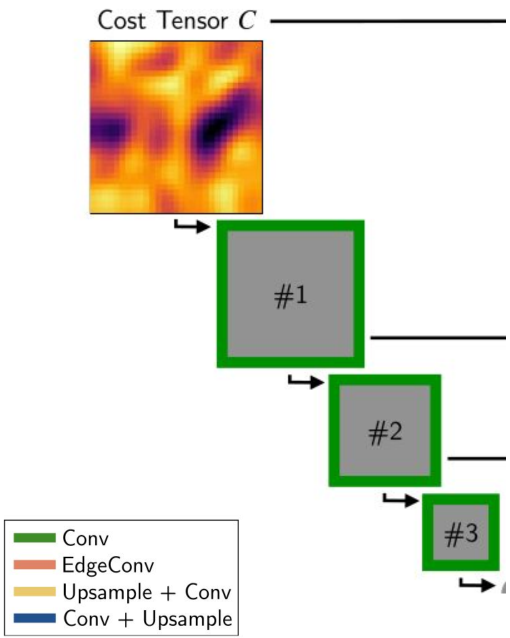


GraphRegNet takes Cost tensor as input and generate displacement vector for each keypoints

U - Net - like architecture consisted of CNN - GNN - CNN



GraphRegNet - Encoder

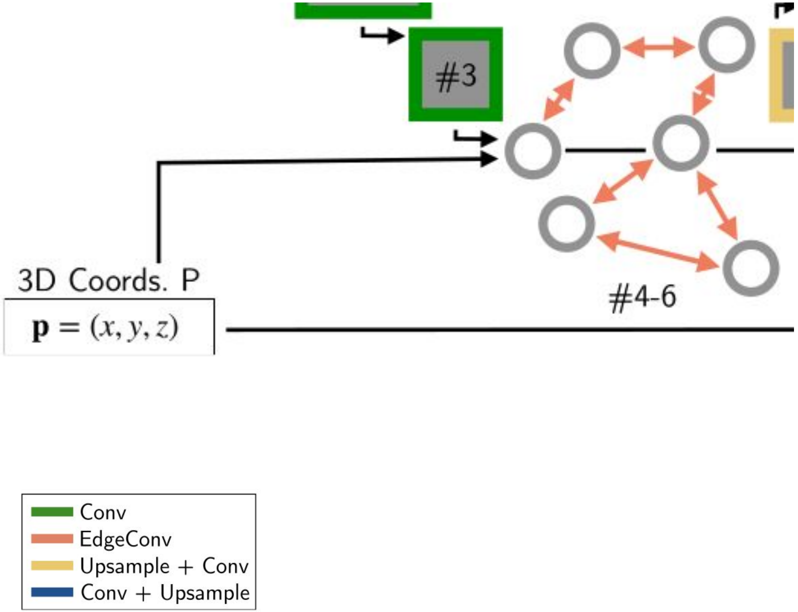


CNN

3 convolutional layers, instance normalization, leaky ReLU

Generate low dimensional displacement embedding

GraphRegNet - GNN



Predicted low dimensional displacement embeddings are concatenated with coordinates of respective keypoints

The concatenated output is distributed across kNN graph of keypoints (k = 15)

Perform three graph convolutions defined as

$$\mathbf{f}_i' = ReLU\left(\underset{(i,j)\in E}{\text{avg}} \mathbf{e}_{ij}\right) \qquad \mathbf{e}_{ij} = h_\theta(\mathbf{f}_i, \mathbf{f}_j - \mathbf{f}_i)$$

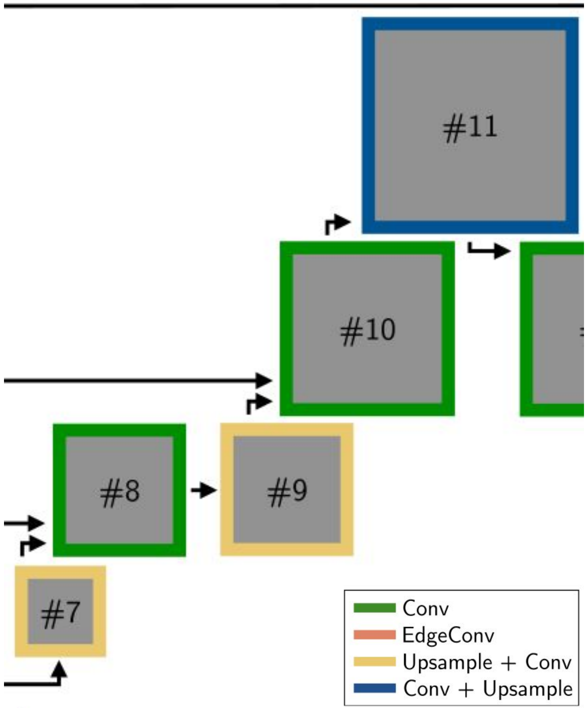
f : feature vector at point keypoint pi

h : inner product of parameters with the
keypoint fi and neighbourhood features fj-fi

Achieves spatial regularization

Helps with smoothing the image

GraphRegNet - Decoder

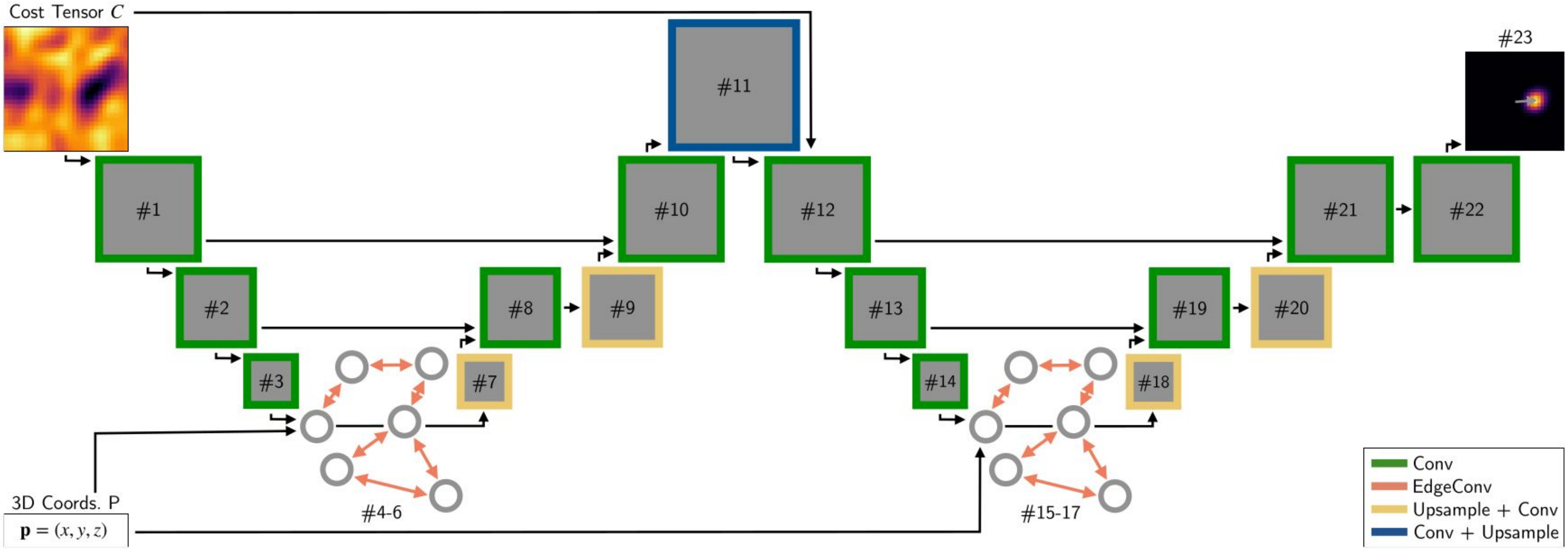


CNN

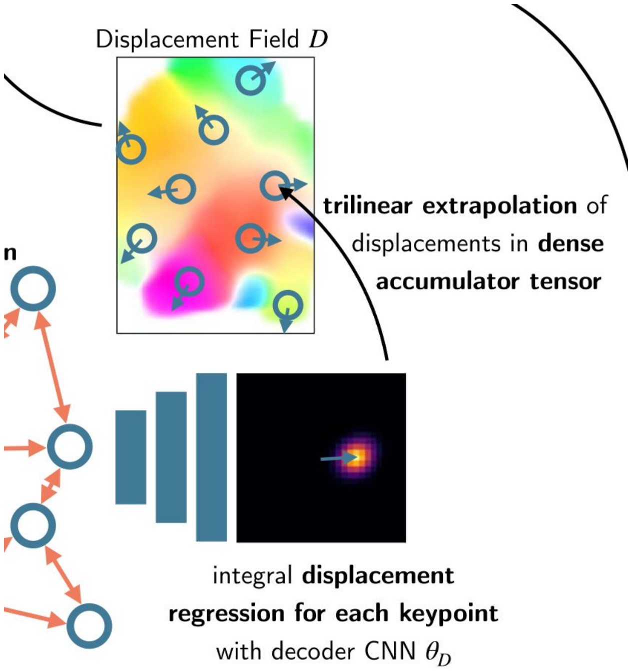
Two Upconvolutions + single convolutional layer

Generates single channel feature map for each keypoint (Hp)

GraphRegNet



GraphRegNet - Sparse to Dense supervision

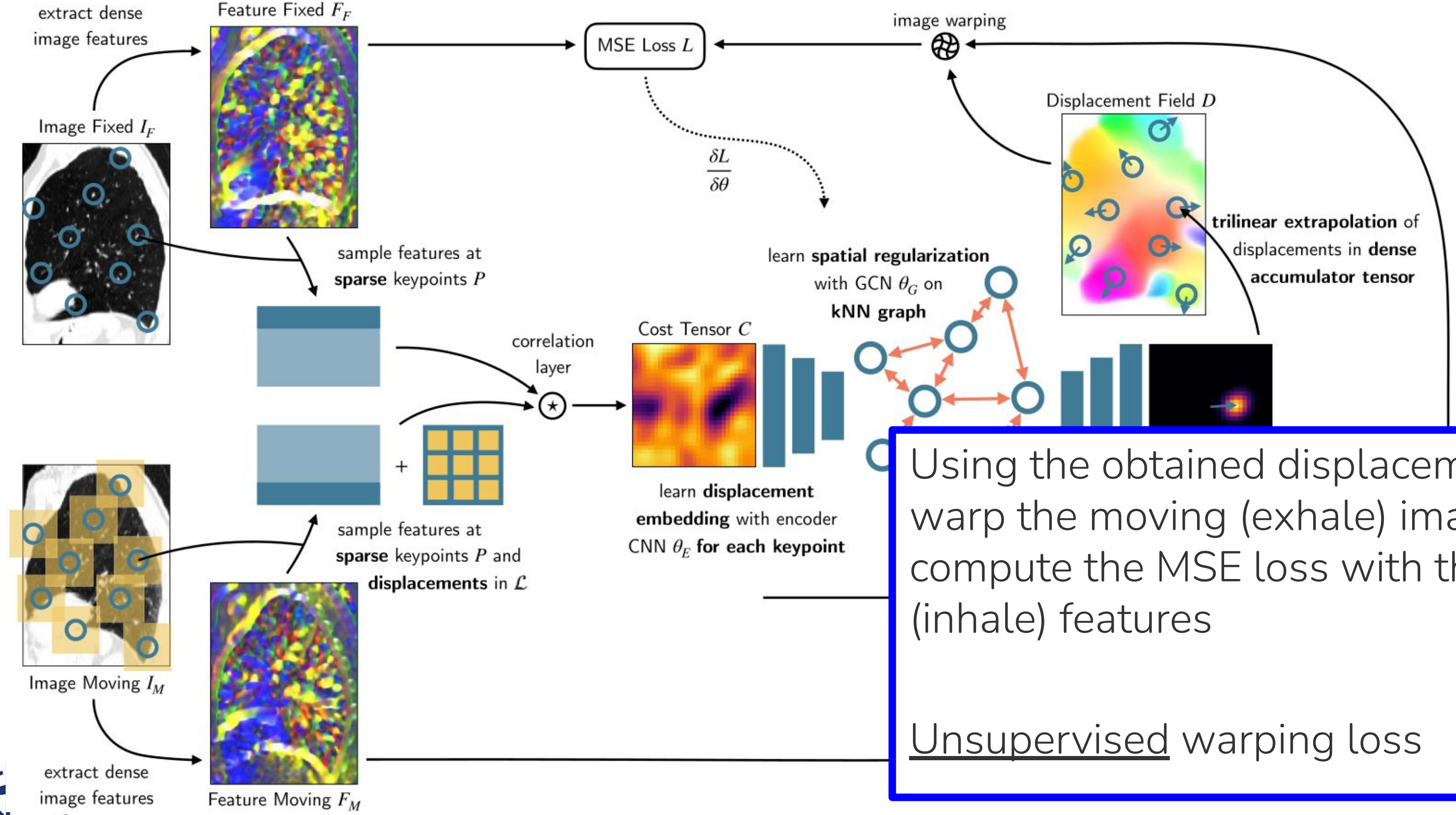


Final displacement vector (**d**) obtained by integrating the generated feature map (Hp) over the displacement search region (l)

$$\mathbf{d} = \sum_{\mathbf{l} \in \mathcal{L}} \mathbf{l} \cdot \tilde{H}_{\mathbf{p}}(\mathbf{l}).$$

The sparse displacement vector (**d**) is accumulated in a dense tensor at respective keypoints using trilinear extrapolation which yields final displacement field ***D***

GraphRegNet - Loss



Using the obtained displacement field ***D***, warp the moving (exhale) image and compute the MSE loss with the fixed (inhale) features

Unsupervised warping loss

Training

Dataset inhale / exhale lung CT scan datasets

- DIR - Lab 4D CT

  Normal resting breathing

- COPD gene dataset

  Breath - hold CT scans, have larger deformations

For training, additional dataset - Empire10, POPI - are added to have total of 45 training pair

5 - fold cross validation used. First fold for hyperparameter tuning

Evaluation

Evaluation metric

- TRE (Target Registration Error) between expert - annotated landmarks
- Jacobian determinants

Evaluation

- Compare the performance with recent DL approaches

  DLIR, Ep18, OSL, LRN, mlVN, BMRF, VM+, LapIRN, FE+, PDD+, MST

  + means the original architecture is modified to fit for both DIR and COPD dataset
- Ablation studies

  RW (Random Walk)

  Noreg (GNN removed)

  Coords (k = 1 in kNN graph)

  SI (no refinement stage)

  Unif (uniformly sample keypoints, non - distinctive keypoints)

Results - TRE Comparison

	init.	DLIR [51]	Ep18 [52]	OSL [53]	LRN [21]	mlVN [20]	BMRF [54]	VM+ [50]	LapIRN [6]	FE+ [55]	PDD+ [16]	MST	ours
4DCT 01	03.89	1.27	1.45	1.21	0.98	1.33		1.46	1.00	2.20	0.90	**0.82**	0.86
4DCT 02	04.34	1.20	1.46	1.13	0.98	1.33		1.51	1.28	3.89	0.91	**0.87**	0.90
4DCT 03	06.94	1.48	1.57	1.32	1.14	1.48		2.31	2.18	2.71	1.06	1.09	1.06
4DCT 04	09.83	2.09	1.95	1.84	**1.39**	1.85		2.72	3.05	2.95	1.66	1.63	1.45
4DCT 05	07.48	1.95	2.07	1.80	**1.43**	1.84		2.69	2.36	3.03	1.68	1.58	1.60
4DCT 06	10.89	5.16	3.04	2.30	2.26	3.57		3.07	1.78	3.36	1.86	1.71	**1.59**
4DCT 07	11.03	3.05	3.41	1.91	**1.42**	2.61		3.01	2.24	3.10	1.94	1.73	1.74
4DCT 08	14.99	6.48	2.80	3.47	3.13	2.62		6.22	2.24	2.94	1.79	1.55	1.46
4DCT 09	07.92	2.10	2.18	1.47	**1.27**	2.70		2.94	2.26	2.86	1.94	1.85	1.58
4DCT 10	07.30	2.09	1.83	1.79	1.93	2.63		3.00	1.90	2.99	2.03	1.90	**1.71**
avg	08.46	2.64	2.17	1.83	1.59	2.19		2.89	2.03	3.00	1.57	1.47	**1.39**
std	06.58	4.32	1.89	2.35	1.58	1.62		2.21	1.89	1.70	1.36	1.26	1.29
sig. level	***							***	***	***	***	***	
COPD 01	26.33						1.51	9.95	6.85	4.89	2.57	1.42	**1.38**
COPD 02	21.79						2.27	9.96	6.90	7.30	4.01	3.42	**2.09**
COPD 03	12.64						1.39	4.41	1.51	2.89	1.46	1.32	1.22
COPD 04	29.58						1.86	7.08	6.38	5.46	2.19	**1.48**	1.58
COPD 05	30.08						1.46	9.19	6.81	5.19	2.22	1.44	**1.37**
COPD 06	28.46						1.40	8.12	4.19	5.53	1.89	1.47	**1.10**
COPD 07	21.60						1.46	7.10	2.73	4.40	1.62	1.37	**1.19**
COPD 08	26.46						1.53	7.92	4.32	3.94	1.72	1.33	**1.19**
COPD 09	14.86						1.34	6.93	3.60	3.57	1.51	1.22	**0.99**
COPD 10	21.81						1.71	9.16	6.59	4.44	2.43	1.55	**1.38**
avg	23.36						1.59	7.98	4.99	4.76	2.16	1.60	**1.34**
std	11.86						0.27	3.75	3.94	4.06	2.63	2.04	1.44
sig. level	***							***	***	***	***	***	

DIR - Lab 4D CT

Improves LRN by 13% (1.59→1.39)

COPD

Better performance in all cases

Results - TRE   Ablation studies

	RW	noreg	coords	sl	unif.	ours
4DCT 01	1.21	1.40	0.86	0.86	0.89	0.86
4DCT 02	1.17	1.64	0.98	0.90	0.93	0.90
4DCT 03	1.37	1.50	1.11	1.13	**1.05**	1.06
4DCT 04	1.52	2.05	1.65	1.61	1.51	1.45
4DCT 05	2.11	2.91	1.73	1.67	1.68	1.60
4DCT 06	1.83	2.19	1.60	1.64	**1.59**	**1.59**
4DCT 07	1.88	2.33	1.67	1.69	1.63	1.74
4DCT 08	1.77	2.88	2.28	1.58	**1.43**	1.46
4DCT 09	2.23	2.23	1.72	1.87	1.72	1.58
4DCT 10	1.97	2.43	1.75	1.97	2.26	**1.71**
avg	1.70	2.15	1.53	1.49	1.47	**1.39**
std	2.38	1.70	1.57	1.30	1.65	1.29
sig. level	***	***	***	***	*	
COPD 01	3.51	4.32	5.50	1.71	1.80	**1.38**
COPD 02	5.26	7.27	9.12	2.75	**2.09**	**2.09**
COPD 03	1.57	1.42	1.40	1.42	**1.18**	1.22
COPD 04	2.51	7.30	4.46	2.06	1.60	1.58
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COPD 07	2.14	2.68	2.99	1.64	1.23	**1.19**
COPD 08	1.64	4.21	2.22	1.54	1.44	**1.19**
COPD 09	2.79	3.02	1.68	1.45	1.13	**0.99**
COPD 10	2.62	7.93	6.95	1.79	1.82	**1.38**
avg	2.79	4.65	4.07	1.76	1.50	**1.34**
std	4.51	5.89	5.57	1.57	1.75	1.44
sig. level	***	***	***	***	***	

- *RW (Random walk)*

~52% improved when using deep learning approach

- Noreg (GNN removed)

~71% improvement when using GNN

- *Coords (k = 1 in kNN graph)*

~67% improvement when exploiting neighborhood information

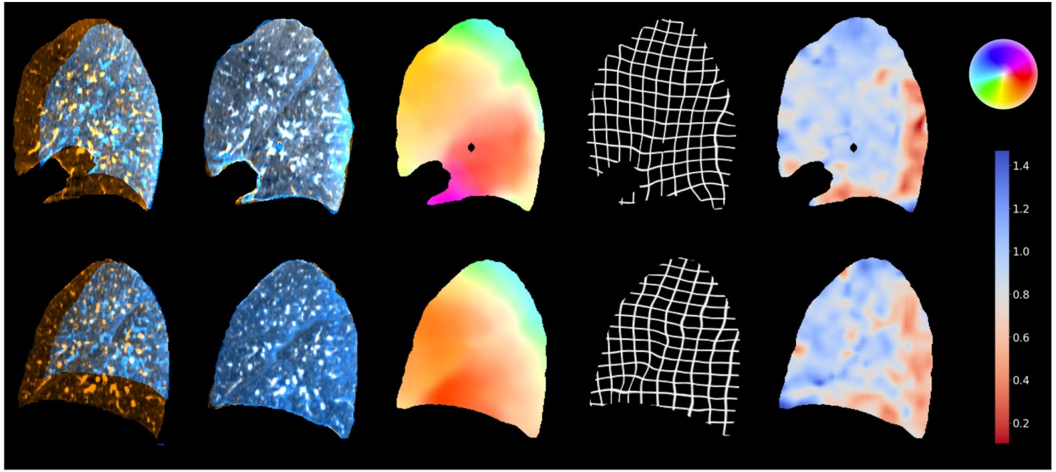
- *Sl (no refinement stage)*

~24% improvement with two level approach

- *Unif (non - distinctive keypoints , uniformly sampled)*

~11% improvement when using distinctive keypoint

Results Jacobian Determinant



	GraphRegNet	VM+	LapIRN	FE+	PDD+	MST
4D CT	0.13	0.11	0.12	0.15	0.10	0.10
COPD	0.21	0.20	0.17	0.32	0.19	0.18

Standard deviation of Jacobian determinant

Fraction of negative values

Shows image foldings

4DCT : 0.02 - 0.21 %

COPD : 0.15 - 0.83%

Standard deviation

Smoothness of the transformation

Closer to 0 : smooth transformation

Results

- Registration accuracy improves LungRegNet(LRN) by 13%

  but fails to reach the accuracy of Rühaak *et al.*
- Shows good improvement with COPD gene dataset
- Good U - Net like architecture design and keypoint based registration shows improvement in TRE by 70 %
- Outstanding improvement in computation time 2s for single registration

  5min (Rühaak *et al*) → 2s

  9 min for single scan pair, previously takes around 3h

Take Home message & Personal Review

- By using sparse keypoint, can decrease computation time

- GraphRegNet shows great potential of fast large deformation estimation algorithm

- By adding a GNN, it helps with smooth transform and spatial regularization

- Future research sounds promising, trying different keypoint/feature extraction might improve the accuracy with a fast registration time
- Code are given on Github, well drawn diagram

Discussion

Why is COPD performing better?

Is it a reliable comparison method of COPD since the architecture is changed?