Automatic Non-rigid Histological Image Registration based on SIFT and RegSnet

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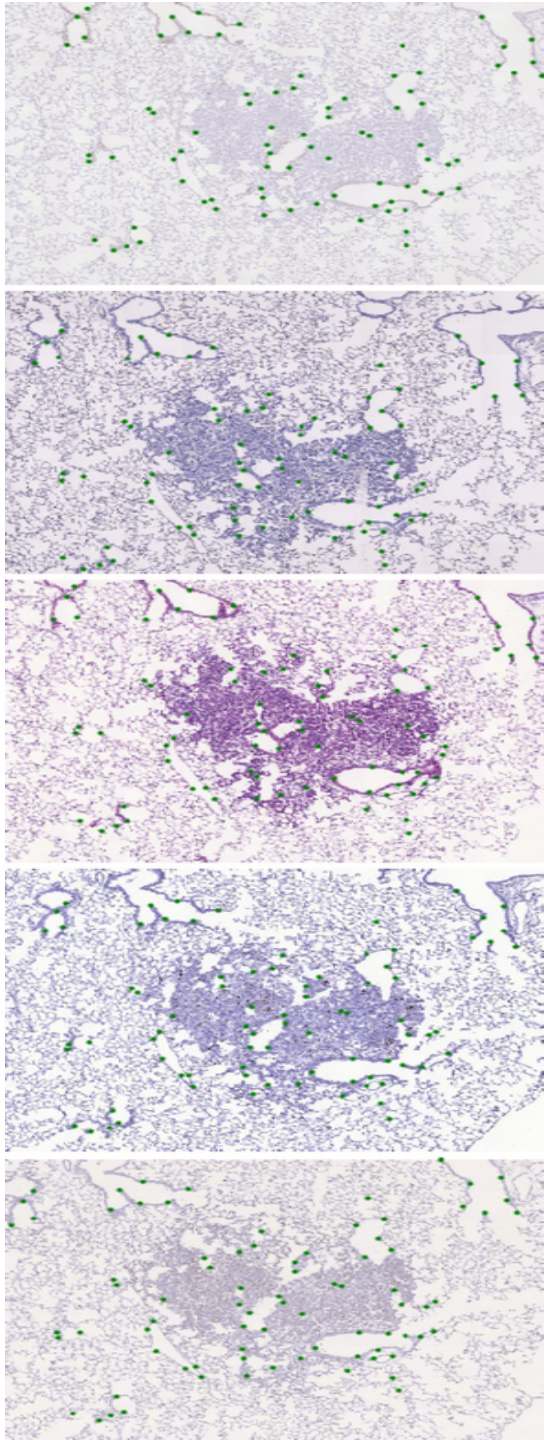
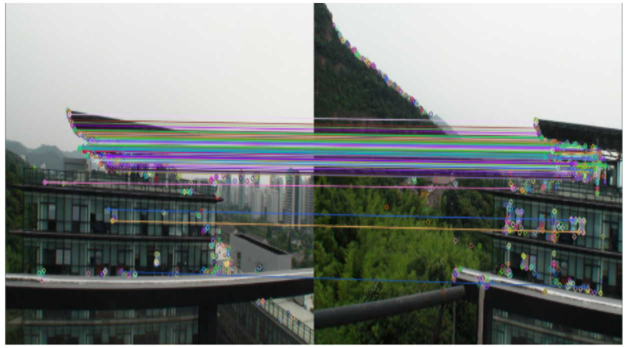
Outline

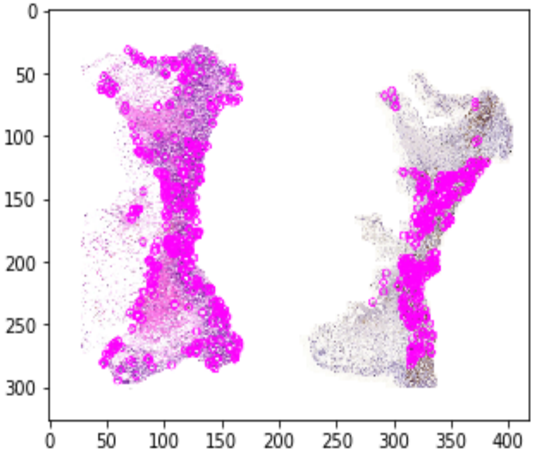
- *Introduction*
- *Develop process*
- *Main Method overview*
- *Result*
- *Limitation*
- *Conclusion*

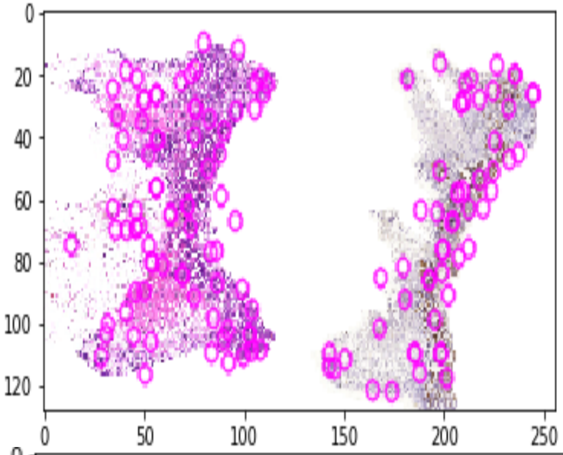


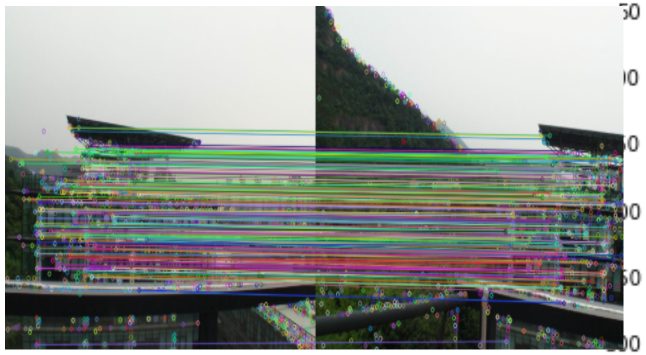
Introduction

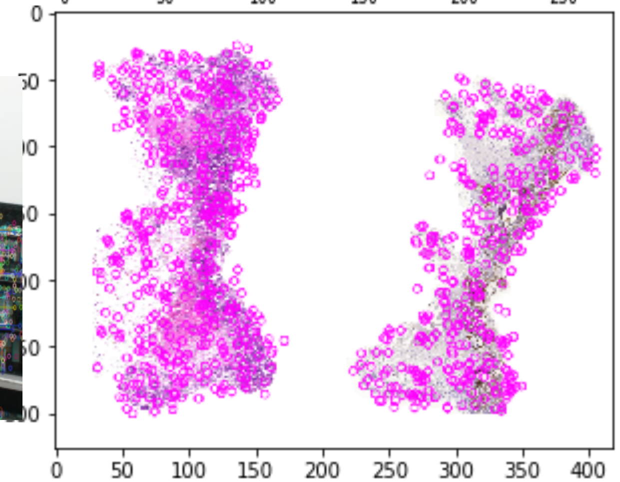
- The importance
- The main task
- Requirement - Elastic(non-rigid)
- Challenge
- Traditional method







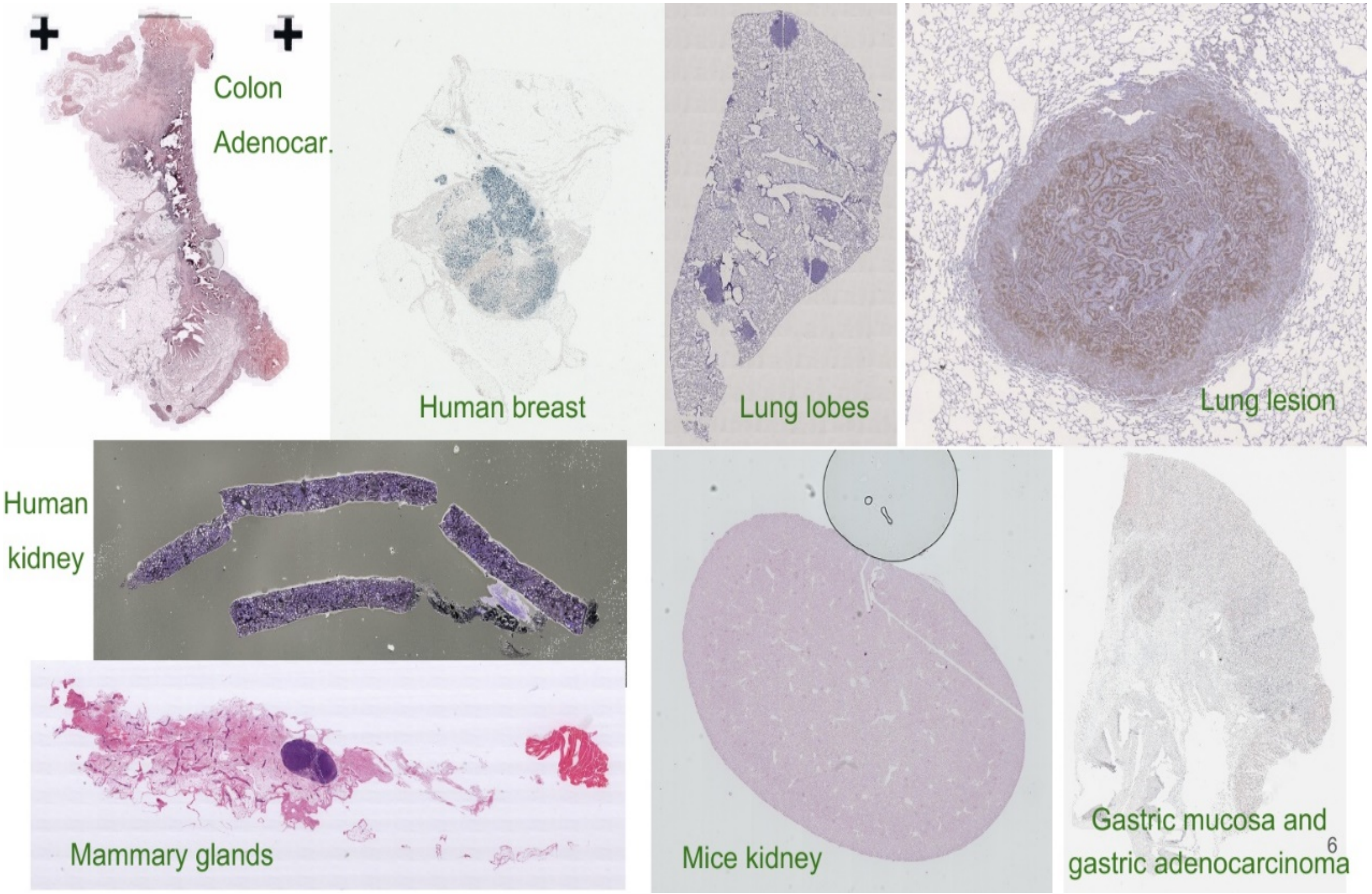


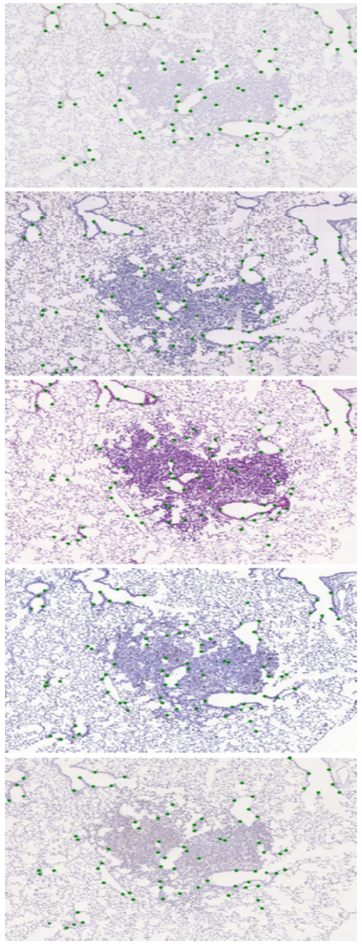


Introduction: Dataset

Name	Tissue	Availability	Resolution [µm/pixel]	Ground truth
lung-lesion_	Lung lesion	Public	0.174	landmarks
lung-lobes_	Whole mice lung lobes	Public	1.274	landmarks
mammary-glands_	Mammary glands	Public	2.294	landmarks
mice-kidney_	Mice kidney	Public	0.227	landmarks
COAD_	COlon ADenocarcinoma (colon cancer)	Public	0.468	landmarks
gastric_	Gastric mucosa and gastric adenocarcinoma tissue fragments	Public	0.2528	landmarks
breast_	Human breast	Public	0.2528	landmarks
kidney_	Human kidney	Public	0.2528	landmarks

Introduction: Dataset

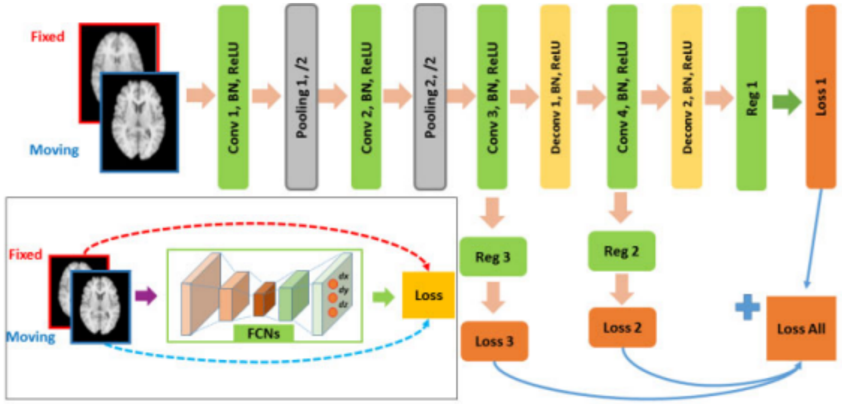


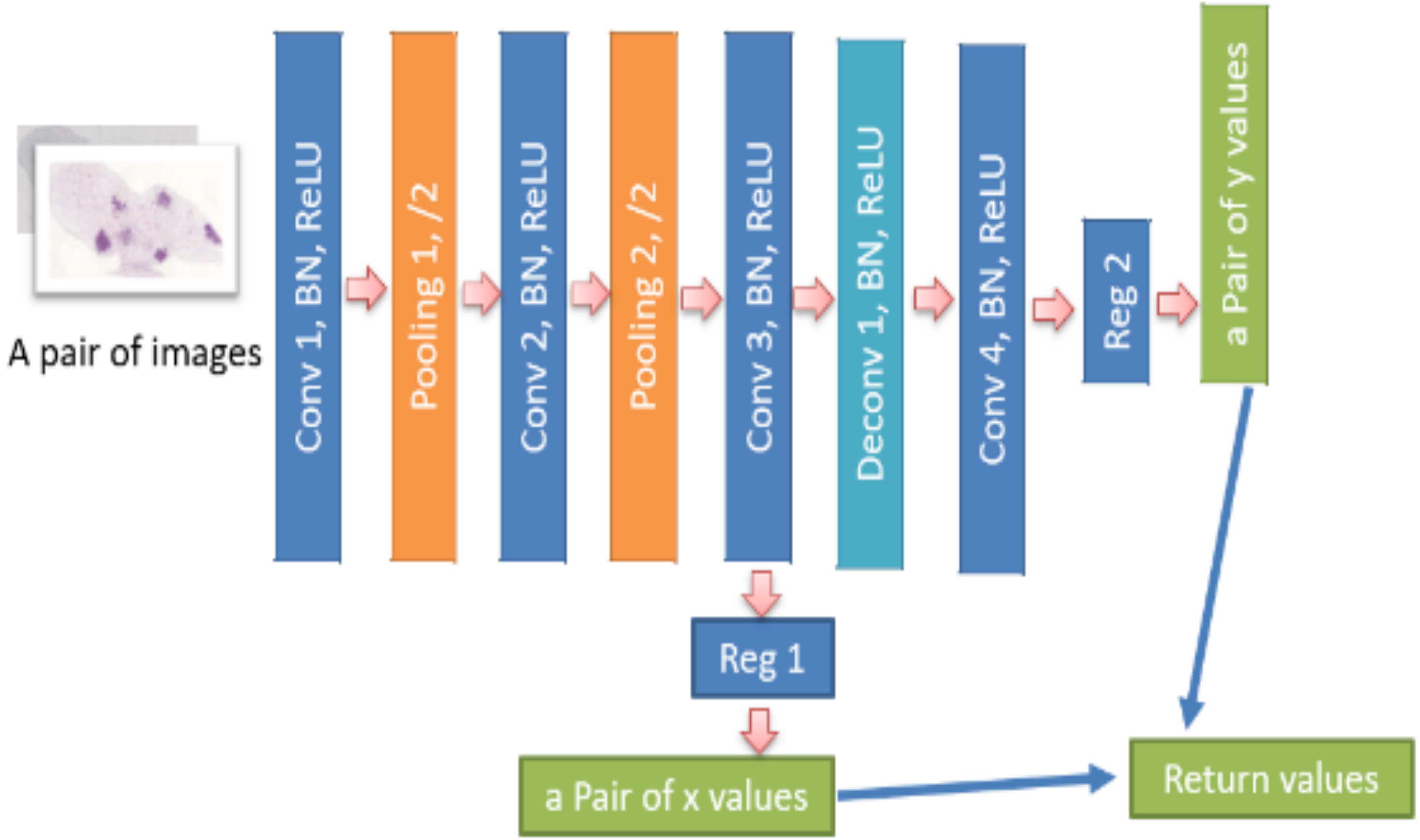


Introduction: Evaluate function

- relative Target Registration Error (*rTRE*): $rTRE = \frac{\mathrm{TRE}}{\sqrt{w^2+h^2}}$
  - Each image: Mean(*rTRE*)
  - Whole dataset: Mean(each image *rTRE*)
- Time: $MeanTime = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} Time(RegistrationApproach(i))$

Develop process: 1st Fully convolutional networks

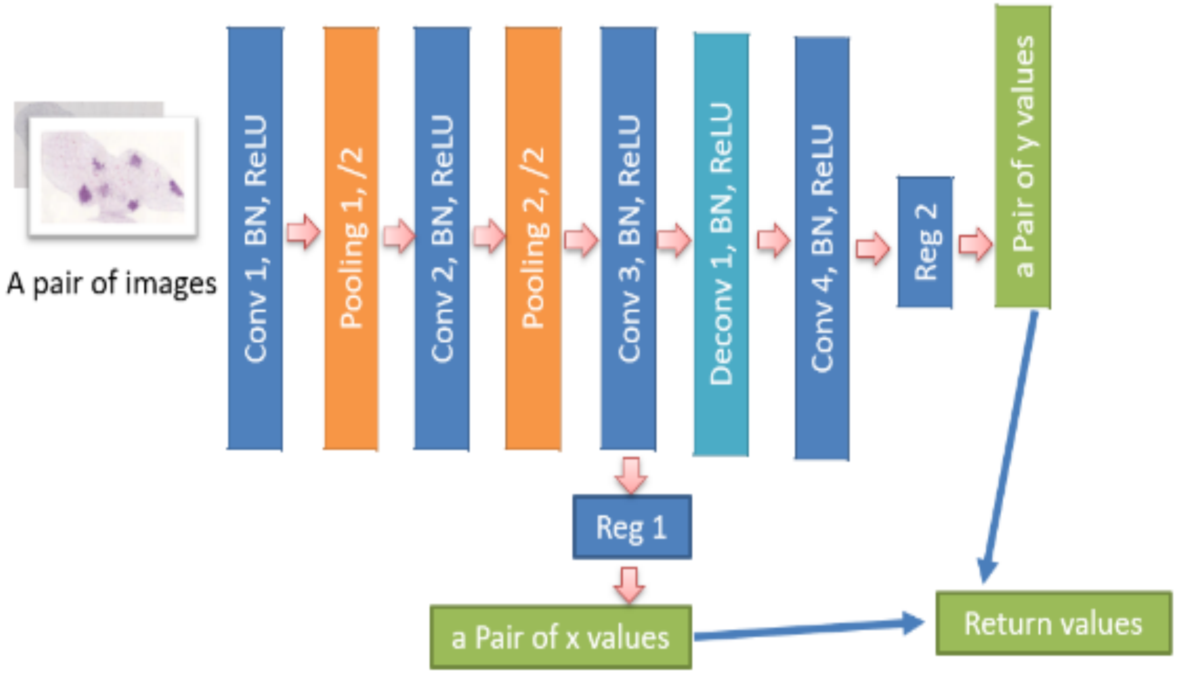


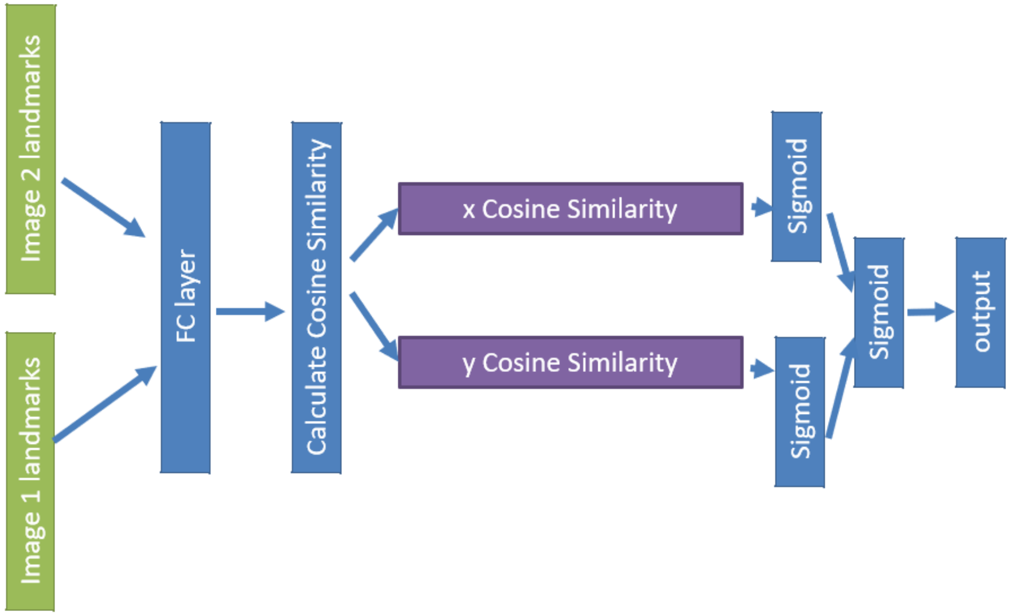


Loss function Mean Square Error:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Develop process: 2nd Generative adversarial network (GANs)





- $\min_{G} \max_{D} V(D,G) = \mathbb{E}_{z\sim P_{data}(z)}[\log D(z)] + \mathbb{E}_{x\sim P_{data}(x)}[\log(1 - D(G(x)))]$

Limitation and optimize

- The GANs generator and FCN is unstable – SIFT
- The SIFT need to filter out meaningless landmarks – Deep learning
- The dataset too small – use small image region instead of whole images
- Deep learning good at classification
- Final method combined SIFT and deep learning classification network

Main Method: Registration

Registration Algorithms: Get N pairs of images from the dataset

for i = 0 . . . N-1 **do**

Process scale-invariant feature transform (SIFT) feature detection to get R^{th} landmarks in source image and L^{th} in target image

1

Expend the landmarks to 16×16 small image regions

2

Process k-nearest neighbors' algorithm (KNN) to get M pairs of the landmarks

for j = 0 . . . M-1 **do**

Put the pairs image into the RegSnet and get score

End for

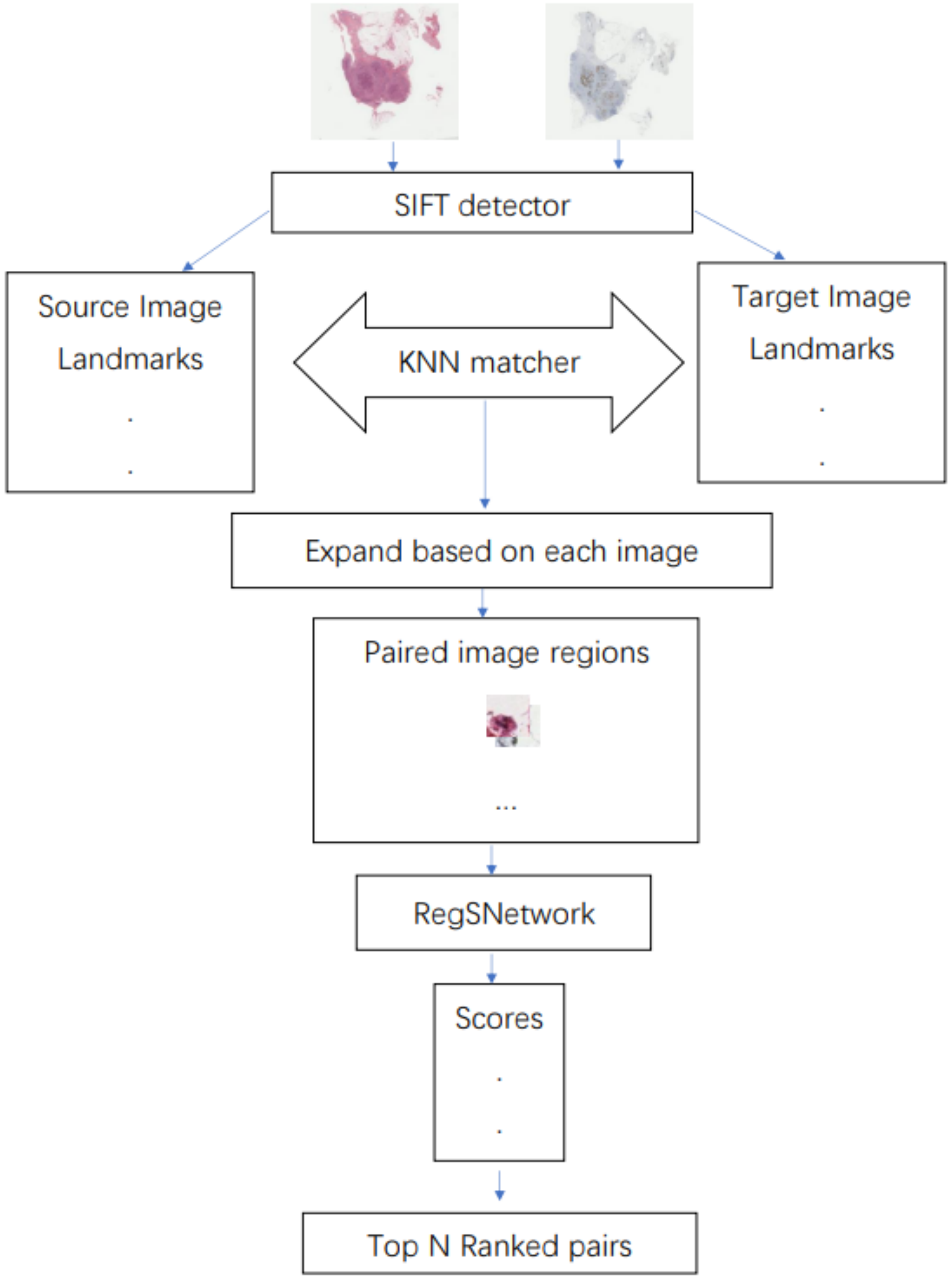
3

Rank all the scores

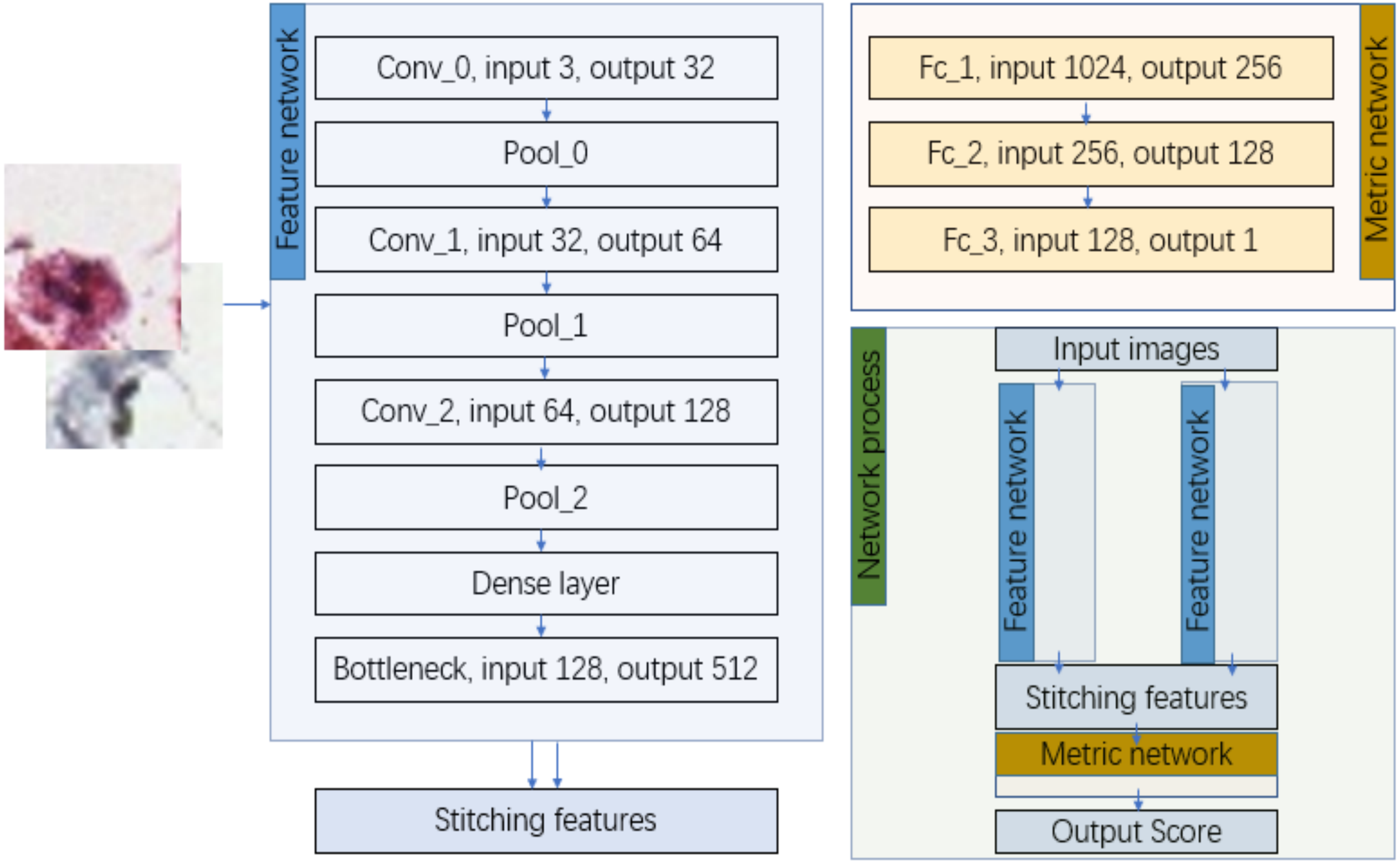
4

Take top K^{th} pairs landmarks as the registration points of each images

End for



Main Method: RegSnet



Main Method: Training

The true training pairs enlarge about 70 times.
The false pairs enlarge about 70 * 70 times.
So, our training dataset is 1068550 pairs small image regions

Train both false and true pairs

Training Algorithms: Get N pairs of images from the dataset

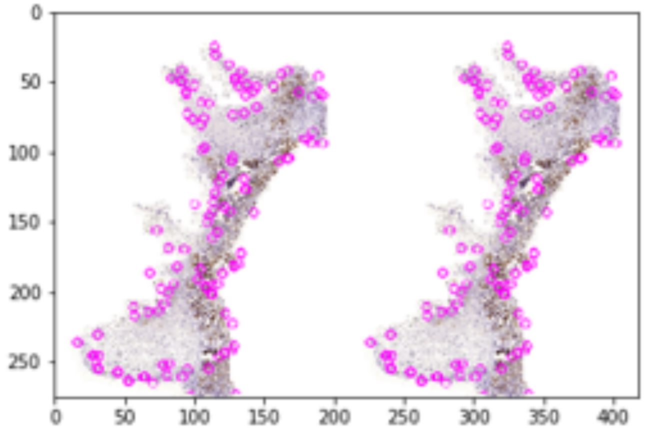
for i = 0 . . . N-1 **do**
  Get M paired corresponding ground truth landmarks
  Expend the landmarks to 16×16 small image regions
  for j = 0 . . . M-1 **do**
    for q = 0 . . . M-1 **do**
      Pair the j^{th} image in the source image patches and q^{th} image in the target image patches
      Put the pairs image into the RegSnet and get result
      If j == q **then**
        Desired output is 1
      else
        Desired output is 0
      End if
      Calculate Cross-Entropy loss (network output, Desired output)
      Optimized the network
    End for
  End for
End for
Return and **save** model

Result

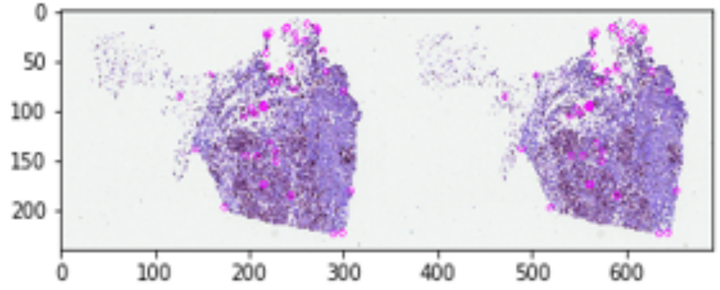
method	Minimum rTRE	Maximum rTRE	rTRE	Average Time
SIFT base line	0.5105	0.6922	0.6205	0.0521
GANs	> 1.0	> 1.0	> 1.0	0.07291
FCN (100 times training)	0.4916	0.9137	0.7814	0.0432
RegSnet	0.003954	0.00816	0.0057252	0.058767

Some compare images - robustness

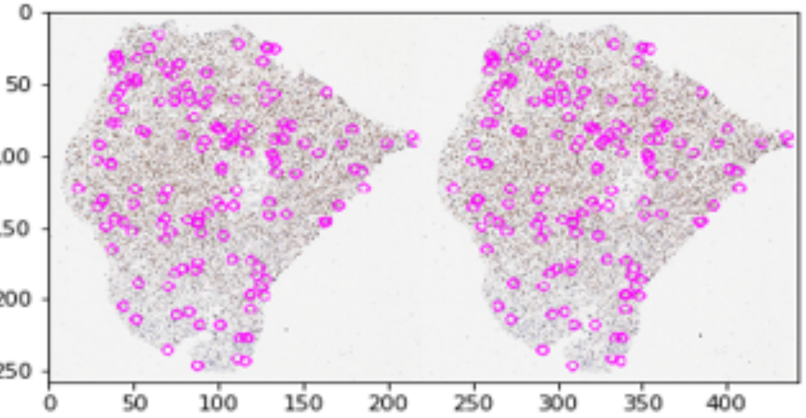
colon cancer



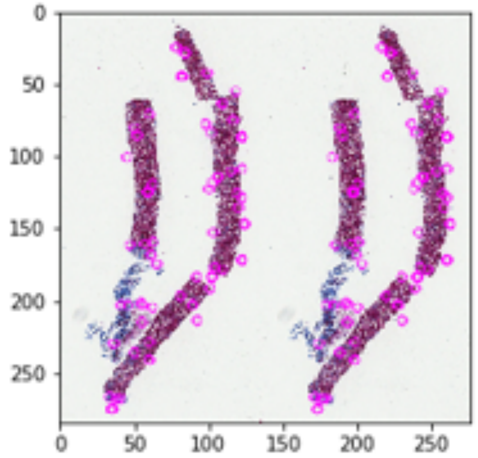
Human breast



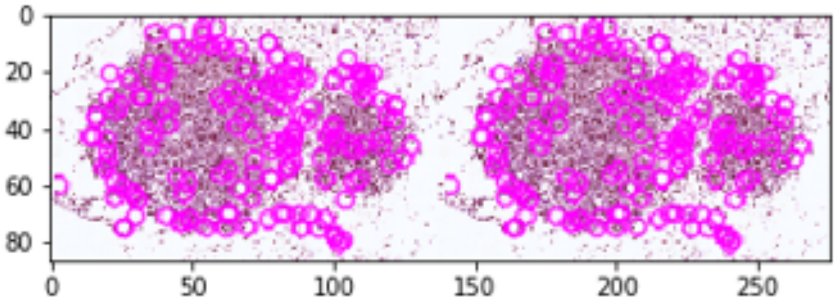
Gastric mucosa and gastric adenocarcinoma tissue fragments



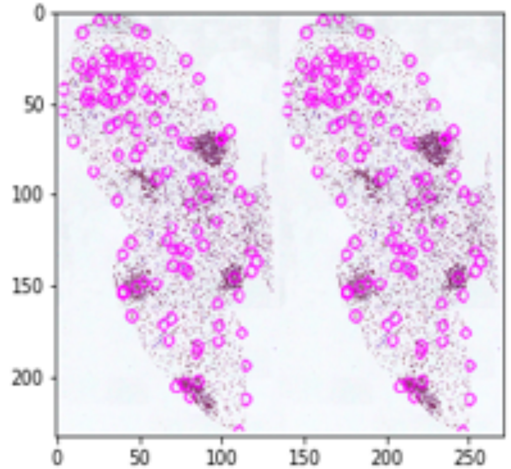
Human kidney



Lung lesion



Whole mice lung lobes



Limitation

- Using local interest point detector may lose meaningful points
- The amount of the generated landmarks is fixed.
- The local interest point detector large influence the performance.
- There might exits a better architecture of RegSnet network
- Due to the complex stages - many local minimums, hard to optimize

Conclusion

- Our SIFT and RegSnet based non-rigid registration approach achieved super accuracy, robustness and speed.
- Overcome the small dataset, histological image issues and non-rigid registration challenges.
- Able to change the inner components to suit for other kinds of registration tasks.

Acknowledgement

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Thanks for listening to my presentation!

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