A Joint Super-Resolution and Deformable Registration Network for 3D Brain Images

Sheng Lan

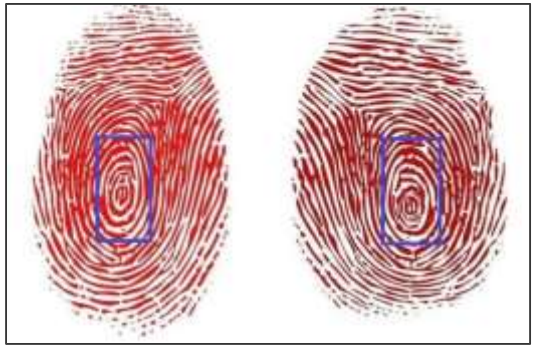
Co-authors:

Bo Yuan, Zhenhua Guo

Tsinghua University

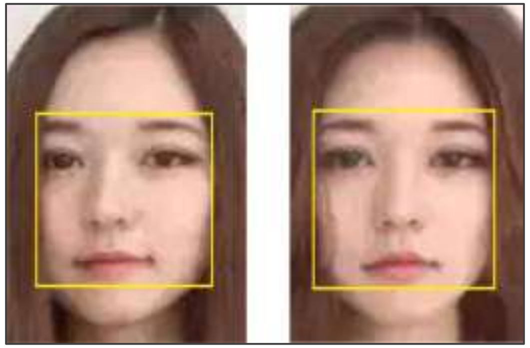
Deformation in Images is Common

Due to the influence of various environmental factors, such as force, direction, skin surface condition and acquisition instrument, the acquired images are often deformed.



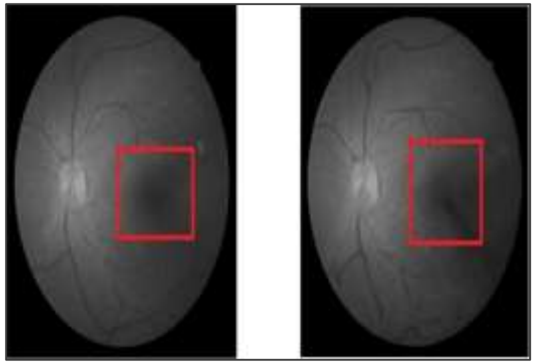
Fingerprint Identification

During the process of fingerprint acquisition, because of different pressing force and angle, even fingerprints of the same person and the same finger can be deformed.



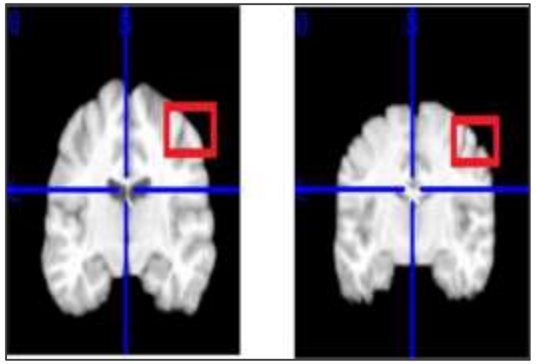
Face Recognition

In face recognition system, with the change of facial expression or angle, the collected face images often has obvious deformations.



Biometric System

Other biological features, such as retina, sweat glands and palmprints, can also deform in different acquisition environment and time.

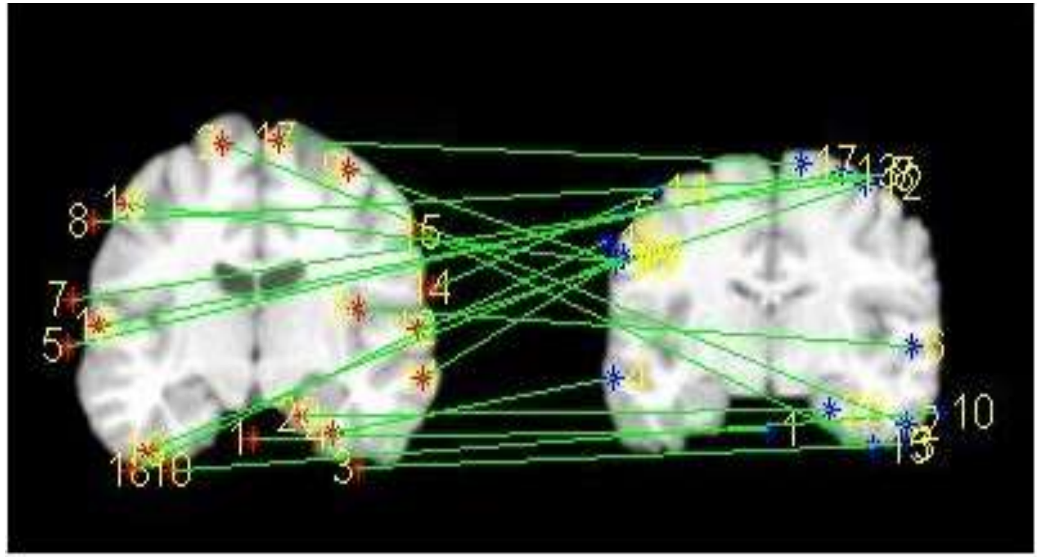


Medical Diagnosis

In the process of medical diagnosis, images collected from organs and tissues before and after the occurrence of lesions often have obvious deformations.

Challenges for Deformable Image Registration

Many various methods have been proposed in this field, which include traditional methods, supervised learning-based methods and unsupervised learning-based methods.

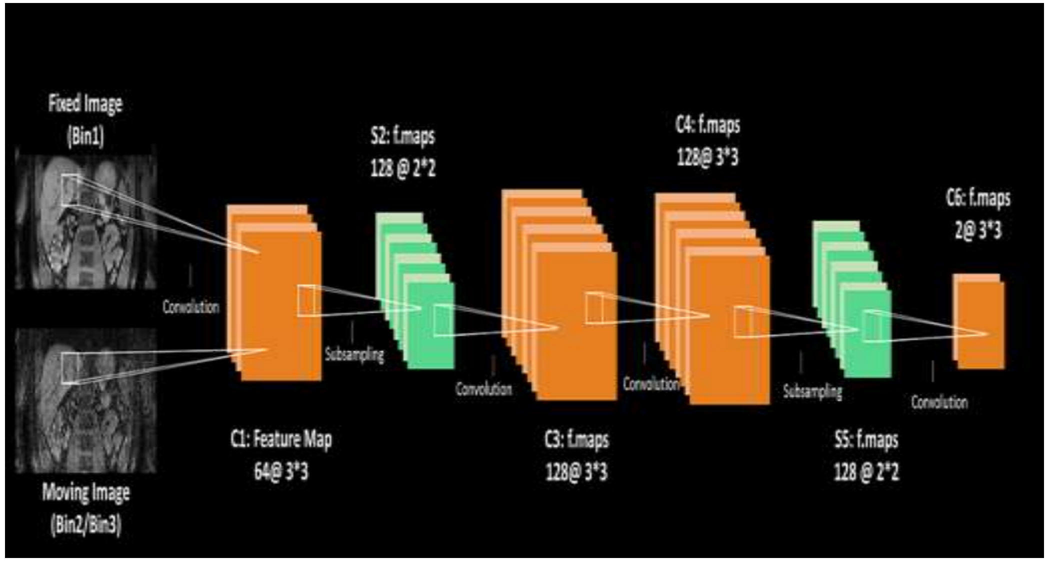


Learning-based Methods

It has strong feature extraction ability and can be applied to many types of images. The supervised learning-based based methods usually need the ground truth labels, which are usually difficult to obtain.

Traditional Methods

Usually rely on hand-engineered features, they may achieve good results for some specific types of images, but can not be general enough to be suitable for all types of images.



Challenges for Deformable Image Registration

Many various methods have been proposed in this field, which include traditional methods, supervised learning-based methods and unsupervised learning-based methods.

Unsupervised learning-based methods:

- A similarity metric is used as the loss function for optimization, and ground truth labels are not needed
- Calculate deformation field based on the extracted features by convolution layers.

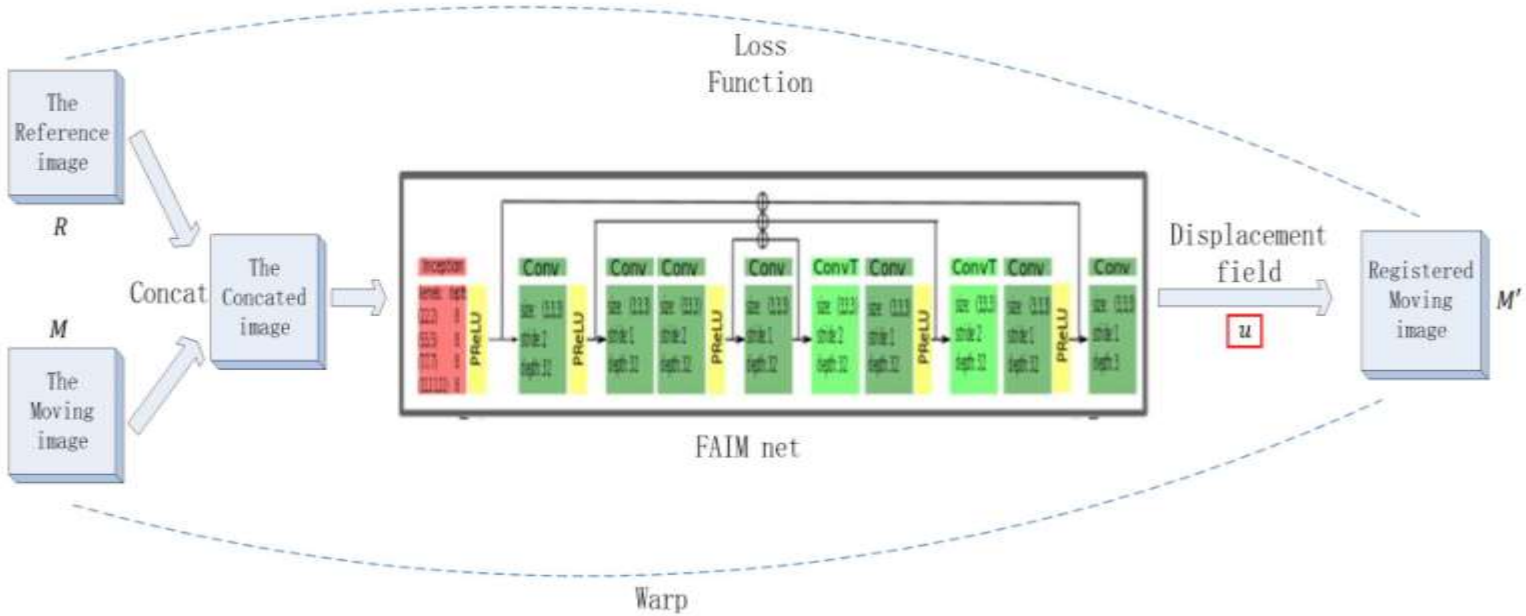


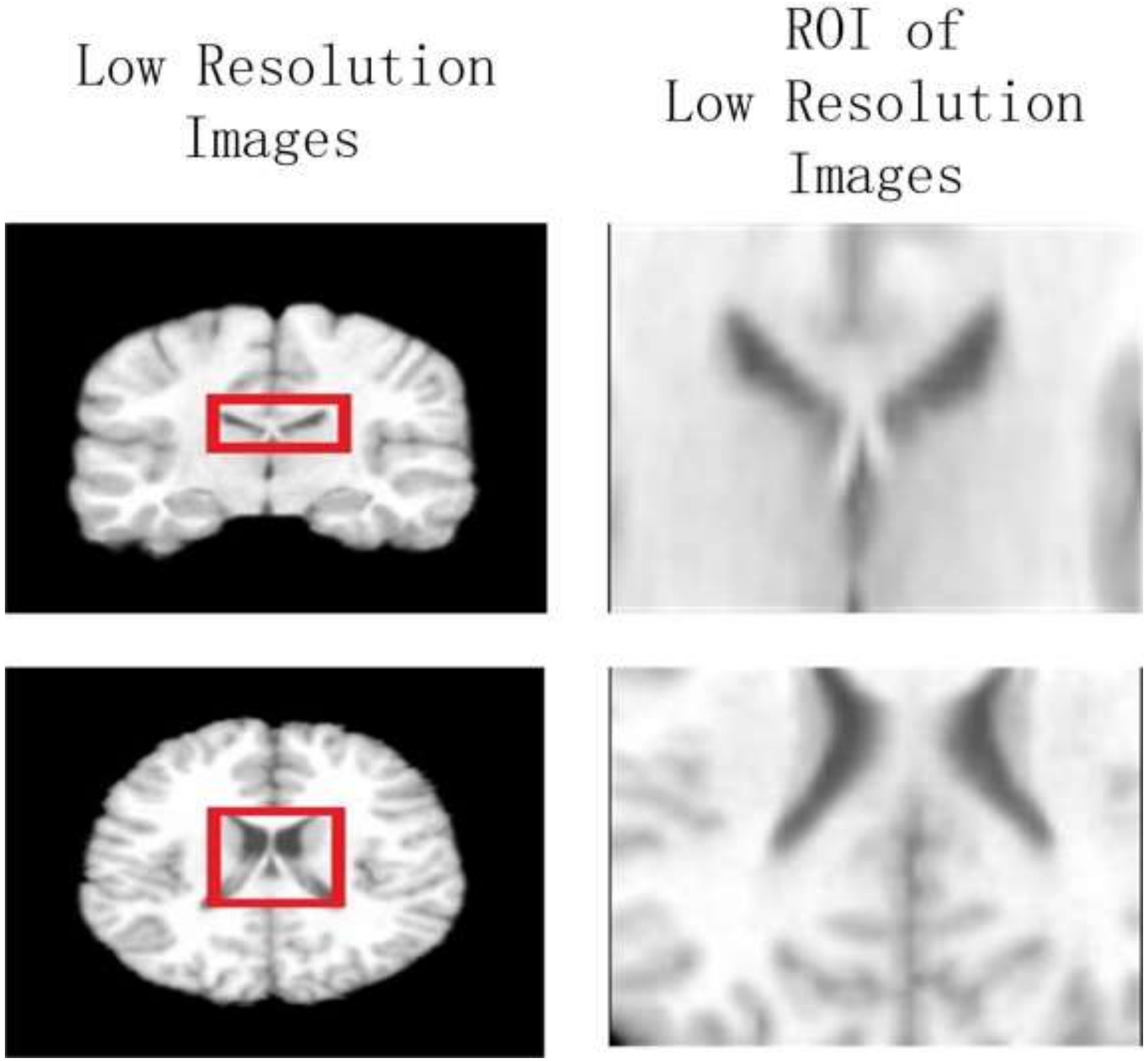
Fig. 2: Structure of the FAIM deformable registration network.

Challenges for Deformable Image Registration

Most of deformable registration methods are under the assumption that the image resolution is high enough.

Challenges of deformable registration methods :

- Due to the limited level of acquisition instruments, the resolution of images is often low, especially for medical image applications
- It is difficult to register low resolution images due to lack of sufficient features



Motivations

A new joint super-resolution and deformable registration network is proposed.

Contributions:

1.Comparison of traditional and deep learning based deformable registration methods.
2. A new joint super-resolution and deformable registration network to aid the registration of low resolution images.

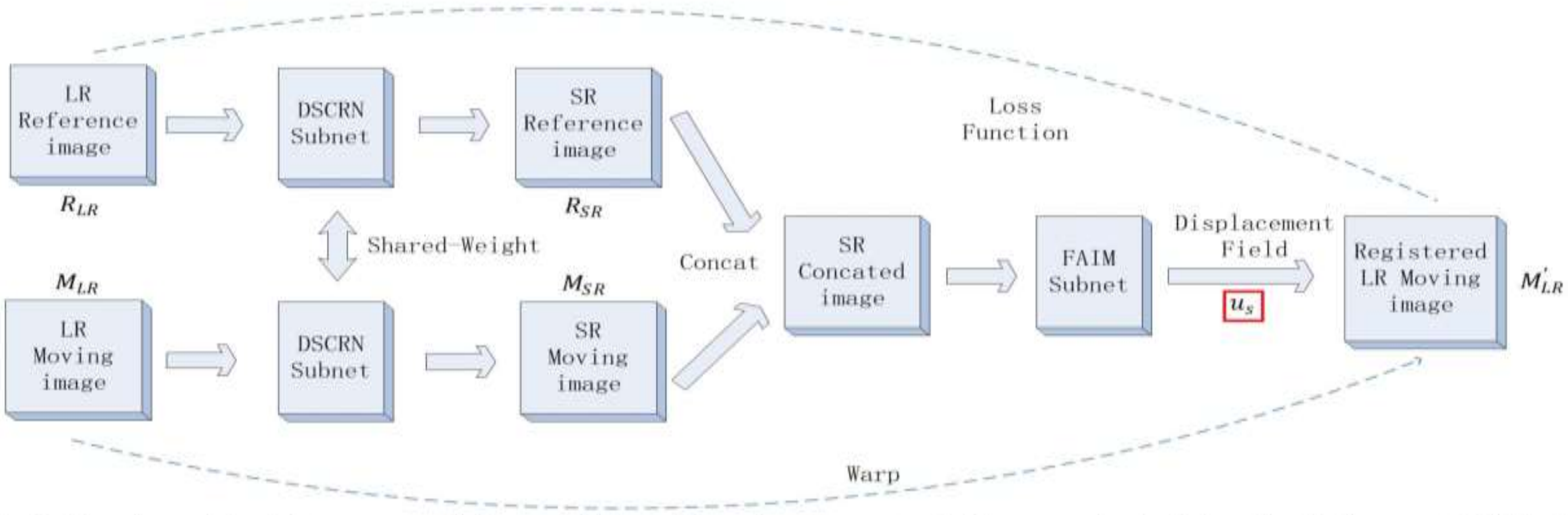
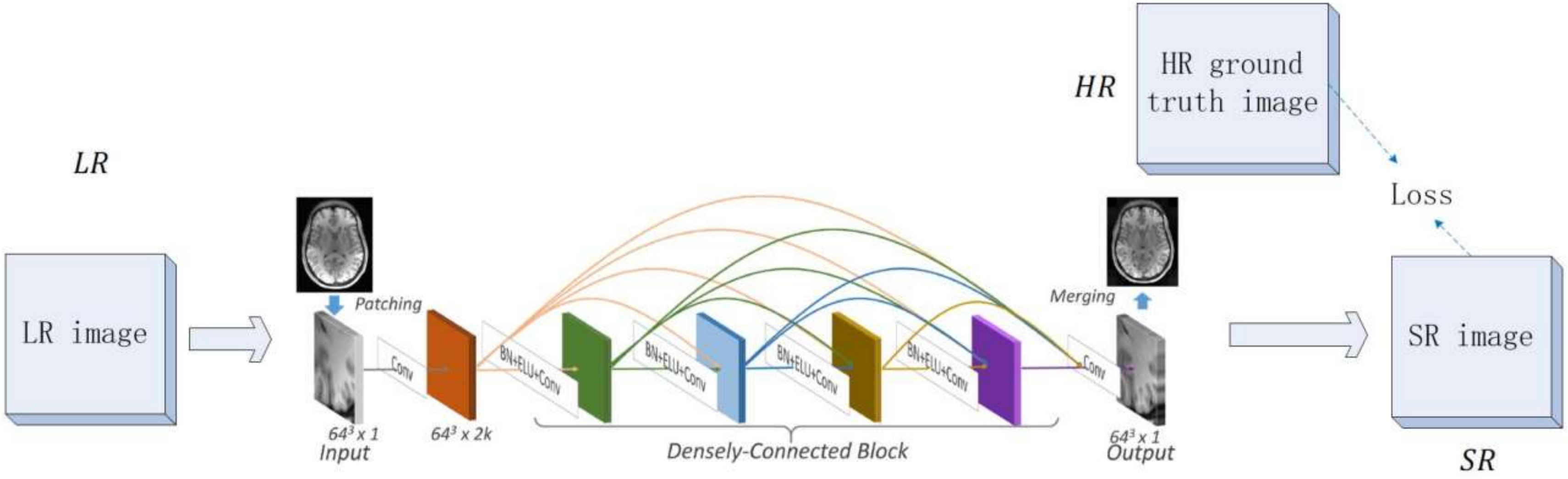


Fig. 3: Flowchart of the joint super-resolution and deformable registration network. The way of calculating the displacement field is changed compared with FAIM method.

Super-Resolution

Super-resolution (SR) typically describes the process of reconstructing high-quality images from images of lower resolutions. It permits acquisition of low resolution (LR) images in order to produce high resolution (HR) images..



The Relation between LR images Y and ground truth HR images X :

$$Y = f(X)$$

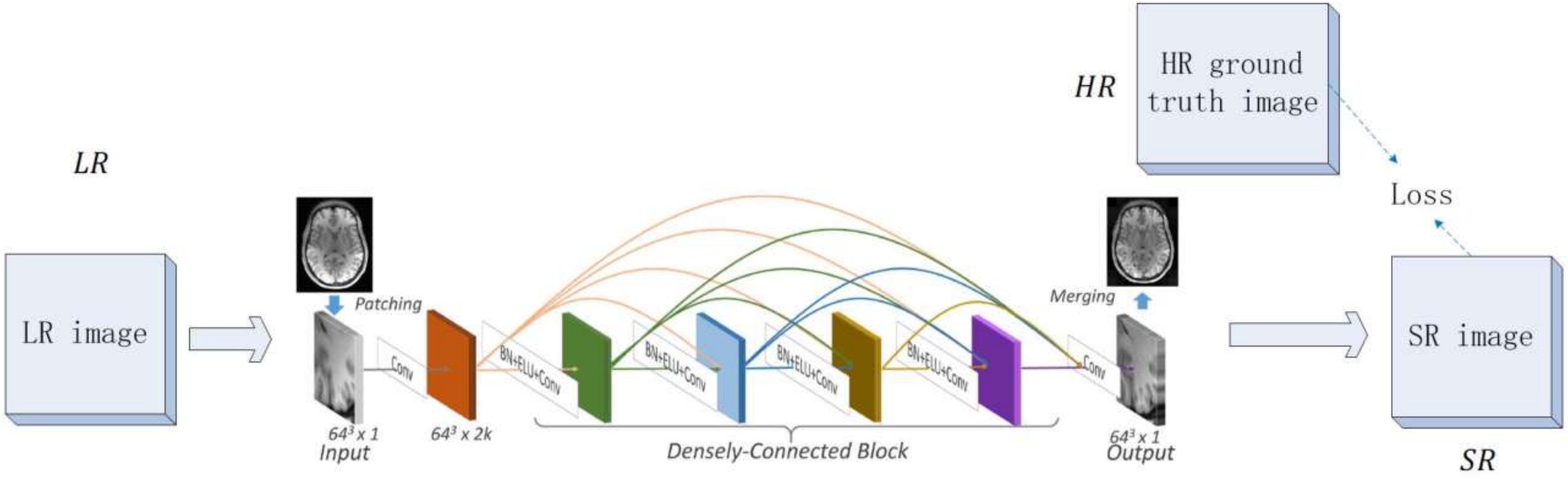
Reconstruction error of the SR process:

$$X = g(Y) = f^{-1}(Y) + r$$

r: the reconstruction error

Super-Resolution

Super-resolution (SR) typically describes the process of reconstructing high-quality images from images of lower resolutions. It permits acquisition of low resolution (LR) images in order to produce high resolution (HR) images..



MSE between the SR output image and the ground truth HR image is used as loss function：

$$L = \frac{1}{hwd} \sum_{i=0}^{h-1} \sum_{j=0}^{w-1} \sum_{k=0}^{d-1} [SR(i,j,k) - HR(i,j,k)]^2$$

h, w, d: height, width and depth of the images respectively

Flowchart of the Proposed Method

First, the low resolution image M_{LR} and R_{LR} are separately fed into the SR subnetworks. After the process of super-resolution, we get the corresponding super-resolution image M_{SR} and R_{SR}. Then the output super-resolution images are stacked together as input of the FAIM subnetwork. In this way, we calculate the displacement field u_s based on super-resolution images (M_{SR} and R_{SR}) instead of original low resolution images (M_{LR} and R_{LR}). Finally, according to the displacement field u_s, the original low resolution moving image M_{LR} is warped to get the registered image M'_{LR}.

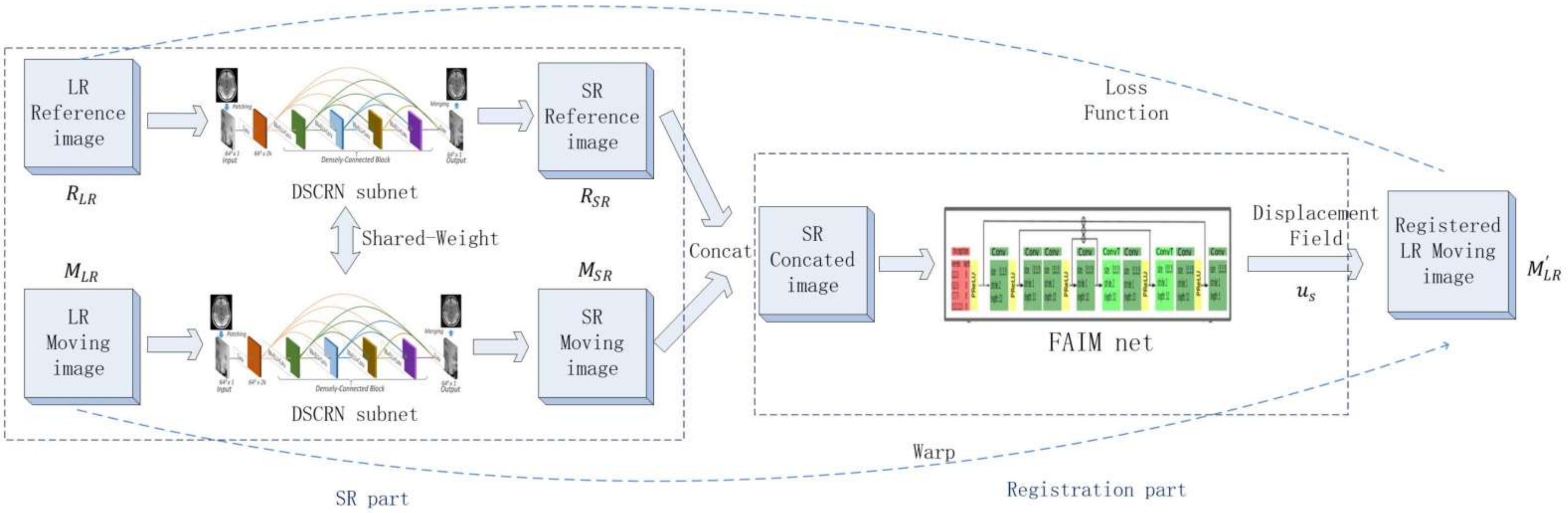


Fig. 4: Unsupervised Alternative Learning of the Joint Network.

loss function:

$$L = 1 - CC(M_{LR} \circ u_S, R_{LR}) + w_1 \|u_S\| + w_2 \|\nabla u_S\|$$

CC: Cross correlation

Displacement Field

The proposed method changes the way of calculating the displacement field u.

Displacement field u_s in the proposed method is calculated based on super-resolution images (M_{SR} and R_{SR}) instead of original low resolution images (M_{LR} and R_{LR}) :

$$M'_{LR} = M_{LR} \circ u_S$$

Loss function of the proposed method :

$$L = 1 - CC(M_{LR} \circ u_S, R_{LR}) + w_1 \left\| u_S \right\| + w_2 \left\| \nabla u_S \right\|$$

By producing the displacement field based on the super-resolution images M_{SR} and R_{SR}, the obtained displacement field u_s can be more accurate than the displacement field u calculated based on original low resolution images M_{LR} and R_{LR}Loss terms of the CNN branch .

Experiment Results

3D T1-weight MRI images from 40 young adults， which are split into 64×64×64 patches as input of the framework.

Comparison among deformable registration results

Dice scores and MSE metrics are averaged with all the subjects

Evaluation	Dice score	MSE score
No registration	0.585	0.488
3D Demons	0.633	0.454
DCSRN + 3D Demons	0.648	0.417
FAIM	0.634	0.456
The Proposed Method	**0.664**	**0.409**

Experiment Results

3D T1-weight MRI images from 40 young adults， which are split into 64×64×64 patches as input of the framework.

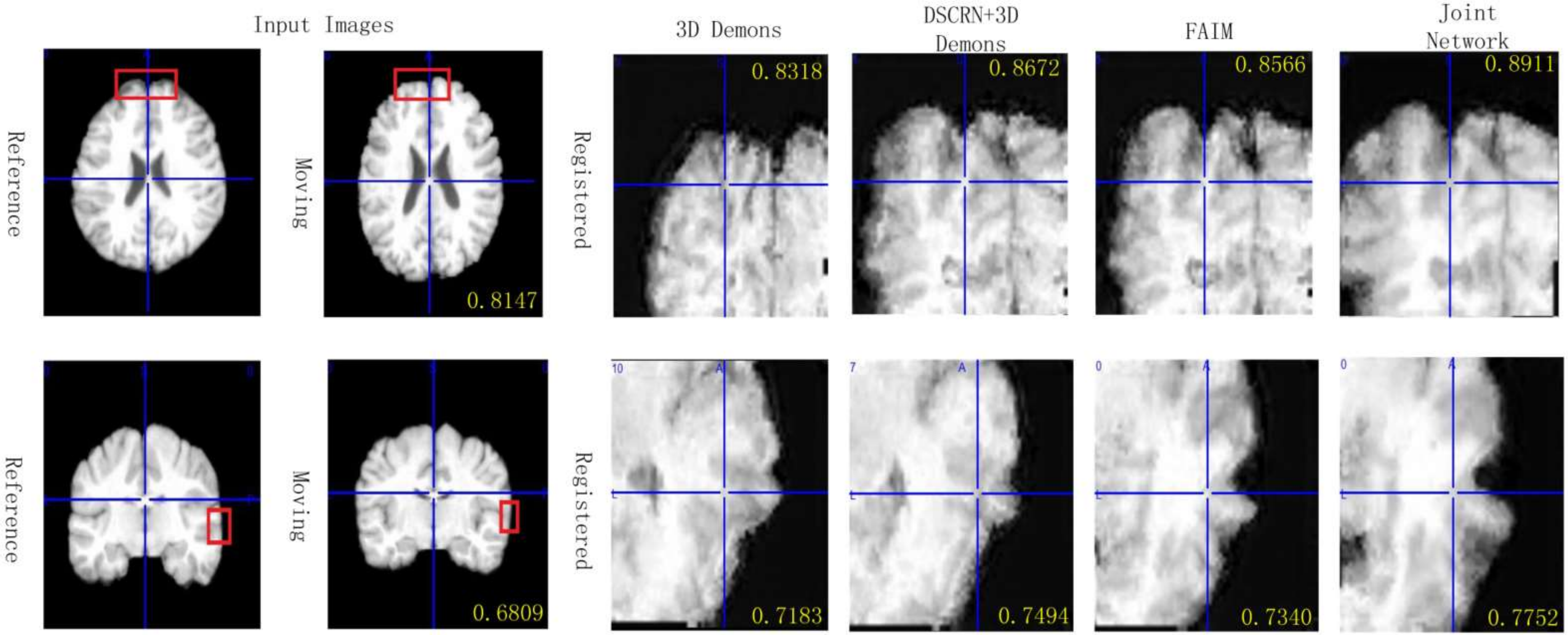


Fig. 5: Visualization of some examples in the LPBA 3D brain dataset. The ROI sections are marked by red box, and Dice score is overlaid on the image.


THANK YOU FOR LISTENING
Speaker：Sheng Lan