3D Pelvic CT-MR Deformable Registration using Unsupervised Cycle-Consistent FCN

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INTRODUCTION

Deformation registration is a time-consuming process in which one medical image undergoes a series of spatial transformations to match another medical image [1-3]. Recently, many studies have demonstrated the feasibility of deep learning methods for image registration [4]. However, there are some problems as following: (1) Supervised registration methods need well-registered clinical medical images that are difficult to obtain for training. (2) Most unsupervised methods ignore the inherent inverse-consistent property of transformations between a pair of images [5].

AIM

The goal of this study is to propose a model of using the Cycle-Consistent Fully Convolutional Network (FCN) for fast 3D CT-MR deformable registration, including: (1) Using Cycle-Consistent method in MR-CT registration to make the deformed image consistent with the reference image, (2) Comparing the registration results with and without Cycle-Consistent

METHOD

A Cycle-Consistent FCN which is divided into **two deformation networks** is used to register CT images and MR images. The deformation network firstly receives multimodal image pairs (i.e., CT image and MR image) and **outputs the deformed transformation**. Then the MR image are deformed to get the deformed MR image. **The CT image and deformed MR are subsequently input into the deformation network again to obtain the reconstructed transformation and reconstructed image pairs**. We standardize all training image data to ensure the consistency of the distribution range of pixel values of all images, and to resample them to a resolution of 1 mm x 1 mm x 5 mm. All the image pixel values are mapped to the range of (-1, 1). **In terms of loss functions, we use regularization loss, cycle loss in CycleGAN and a metric called modality independent neighborhood descriptor (MIND)** to perform deformable registration on CT-MR images.

RESULTS

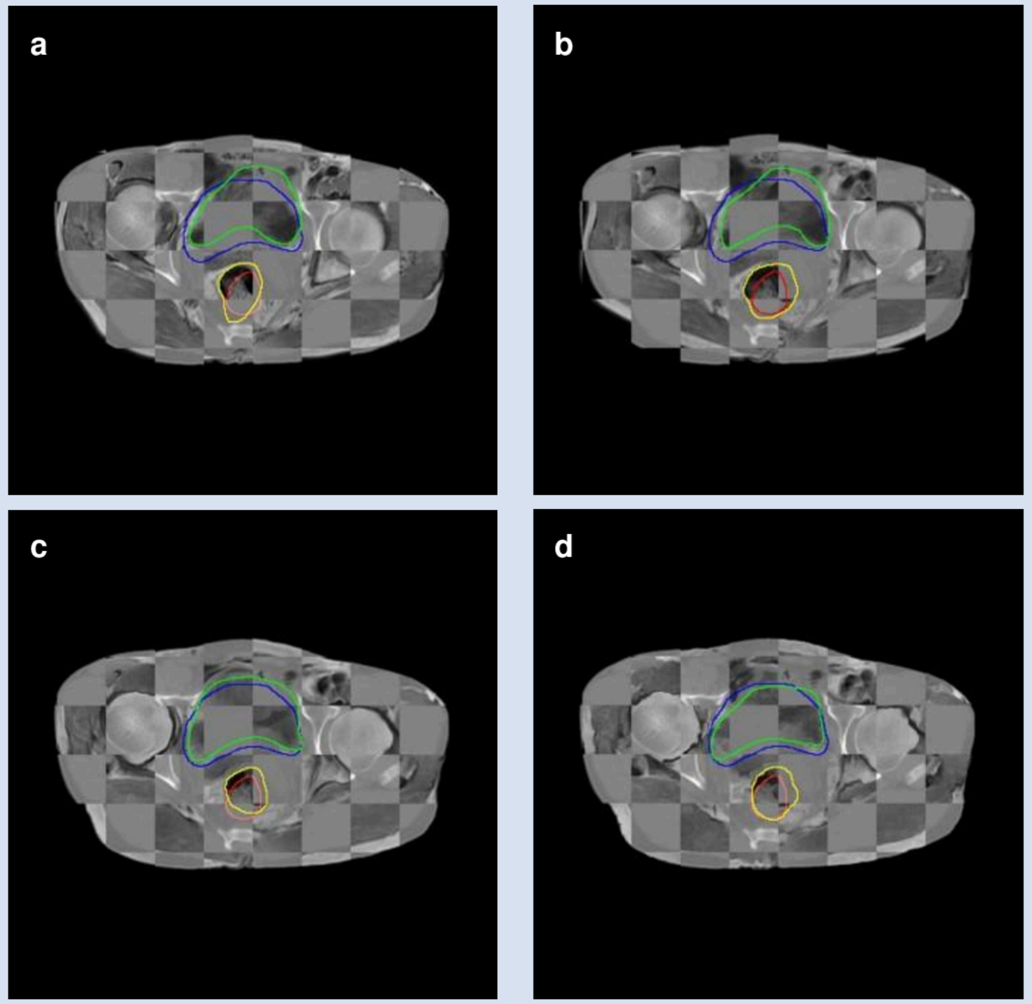

Figure 1. Fusion images of CT and MR before and after registration with different methods. a the fusion image of CT and MR after registration using Elastix; b the fusion image of CT and MR after registration using MIM; c the fusion image of CT and MR after registration using FCN with Cycle-Consistent; d the fusion image of CT and MR after registration using FCN without Cycle-Consistent. The red, blue, yellow, green contours represent the rectum of fixed image, the bladder of fixed image, the rectum of deformed moving image and the bladder of deformed moving image. *means the maximum value.

Seventy-four pelvic cases with MR and CT images are studied. Among them, sixty-four cases are used as training data set and ten cases are used as test data set. For evaluation purposes, we calculated the Dice coefficient of Rectum and Bladder before registration and after registration. Table.1 and Table.2 show the results in ten test cases and the * indicates the best Dice value. The performance of the proposed method is compared with that of Elastix software, MIM software and FCN. The results show that the proposed method achieved the best performance among the four registration methods in terms of registration accuracy and the method was more stable than others in general. In terms of average registration time, Elastix took 64 seconds, MIM software took 28 seconds and the proposed method was found to be significantly faster, taking less than 0.1 seconds.

Table.1 Dice values and registration time of Rectum in pelvic cases before registration, after registration using Elastix software, MIM software, proposed method and FCN.

Dice of Rectum	Before Registration	Elastix	MIM	Proposed method	FCN
Case1	0.26	0.71	0.68	0.71	0.76*
Case2	0.42	0.82*	0.62	0.70	0.75
Case3	0.48	0.81*	0.76	0.75	0.75
Case4	0.59	0.66	0.72	0.87*	0.86
Case5	0.54	0.82	0.84*	0.77	0.79
Case6	0.10	0.69	0.53	0.75*	0.44
Case7	0.46	0.88	0.67	0.85	0.89*
Case8	0.53	0.60	0.69	0.91*	0.74
Case9	0.60	0.82	0.89*	0.89*	0.88
Case10	0.35	0.80	0.88*	0.83	0.75

Table.2 Dice values and registration time of Bladder in pelvic cases before registration, after registration using Elastix software, MIM software, proposed method and FCN.

Dice of Bladder	Before Registration	Elastix	MIM	Proposed method	FCN
Case1	0.54	0.77	0.77	0.87*	0.86
Case2	0.66	0.82	0.69	0.86*	0.81
Case3	0.75	0.91	0.86	0.92*	0.91
Case4	0.33	0.80	0.86*	0.83	0.80
Case5	0.76	0.84	0.89*	0.89*	0.89*
Case6	0.50	0.89*	0.82	0.86	0.83
Case7	0.63	0.79	0.87*	0.87*	0.87*
Case8	0.63	0.89*	0.79	0.84	0.83
Case9	0.40	0.74	0.82	0.82	0.85*
Case10	0.53	0.83*	0.80	0.83*	0.73

CONCLUSIONS

Iterative calculation is the most common method in medical image registration, but it is relatively time-consuming. In this paper, a 3D MR-CT image deformation registration method based on Cycle-Consistent FCN is proposed. Compared with other existing image registration networks, this model was end-to-end and completely unsupervised. The results show that the proposed model in this study can accurately register multi-modal medical images and greatly improve the registration speed.

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