

Rigid and Deformable Image Registration Analysis in Radiation Therapy based on SIFT Method

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1. Introduction

3D and 4D images of the patient are often acquired during the treatment in Image Guided Radiation Therapy (IGRT), aiming to increase the precision of the dose delivery. This process allows checking the correct positioning of the patient on the table treatment and also whether there is a need to adapt the treatment planning. To determine the patient's displacement concerning the planned position, image registration is widely used in radiation therapy^{1,2,3}.

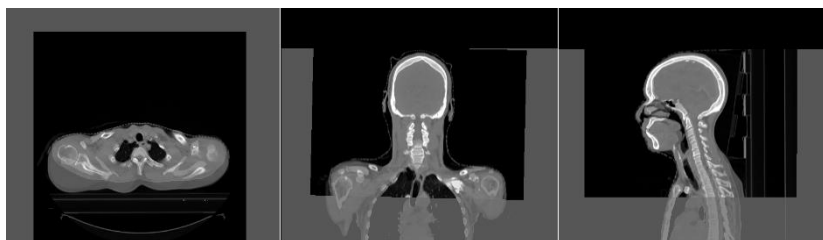
It is common for clinics to have software that performs rigid or deformable registration between two images of the same patient, and quantitative error analysis of the performed registration must be carried out so that the accuracy of the treatment is not greatly affected. A very efficient way to evaluate the performance of image registration is based on a large number of reference points distributed in the used images. Such points are usually selected manually by an experienced professional, however, SIFT (Scale Invariant Feature Transform) technique is a method that enables the automation of the extraction of stable points in images, which have properties that are invariant to different types of transformation of the image^{2,3,4,5}.

The scope of this work is to assess the difference between a rigid and a deformable registration between two 3D computed tomography (CT) patient scans, using points found by SIFT technique in the images.

2. Methodology

For this work, CT images of a patient undergoing head and neck (HN) radiation therapy, obtained from The Cancer Imaging Archive (TCIA)⁶ image bank, were used (512 x 512 x 225 voxels with a spacing of 1.27 mm x 1.27 mm x 2.00 mm). To perform both rigid and deformable registration, the patient's most recent CT was defined as the reference image and, the oldest CT, in which was created the initial treatment planning, as the moving image to be registered. The Elastix module in 3Dslicer software⁷ was then used to perform separately rigid and deformable registration between the images.

In Figure 1, it is possible to visualize an axial, a coronal and a sagittal view of the image resulting from the registration superimposed on the reference image, for the rigid (a) and deformable registration (b).



(a)

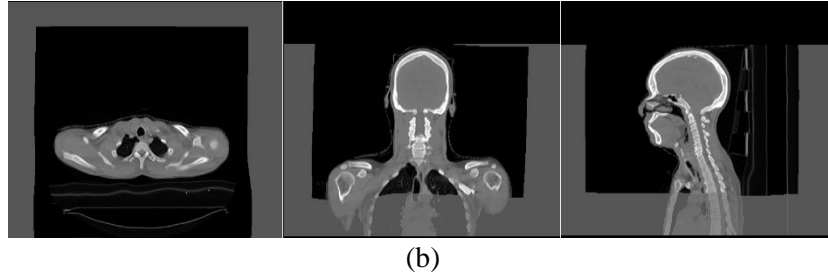


Figure 1: Superimposed reference image and image resulting from (a) rigid and (b) deformable registration.

In order to extract stable points on both images from both registrations, an in-house code was used. The code was developed in Python language⁸, based on SIFT technique⁵ to be applied to 3D medical images, and was duly validated. Using the code, it was possible to identify matching stable points between the reference image and the registered image and use them to estimate an error value for each type of registration. This value was calculated by spatial distance between the points on the images.

The developed code also calculates and returns the mutual information (MI) value between the provided images. Thus, the code returns two types of quantitative analysis of the registration²: one based on image characteristics through reference points and the other based on image voxel intensity (MI).

3. Results and Discussion

The main results obtained from the analysis performed using the in-house code are shown in Table I. For the images resulting from the rigid registration, the code returned 17 stable and matching points uniformly distributed across the images. A mean error estimate of 4.95 mm was obtained for this registration, with a standard deviation of 3.88 mm, and, among the points, the largest error found was 14.61 mm. For the images resulting from the deformable registration, the code returned 19 matching points, from which it was possible to obtain an estimated mean error of 2.44 mm, with a standard deviation of 1.90 mm, and a maximum error of a given point of 7.88 mm.

Table I: Results obtained from the analysis of rigid and deformable registrations.

Registration	N° points SIFT	Mean error (mm)	Max. error (mm)	MI
Rigid	17	4.95 ± 3.88	14.61	0.559
Deformable	19	2.44 ± 1.90	7.88	0.603

In Figure 2, it is possible to verify slices containing matching points (in red) between the reference image and the image resulting from (a) the rigid and (b) the deformable registration. Figure 2-a shows the pair of points that resulted in the maximum error of 14.61 mm for the rigid registration. It is important to highlight, even in Figure 1, that, in this region of the patient's shoulders, the rigid registration had a very poor alignment, which was better aligned in the deformable registration. It is possible to see in Figure 2-b that, for the same region of the shoulders, a pair of points in the deformable registration presented an error much smaller of 1.27 mm, a value that is below the voxel size of the images.

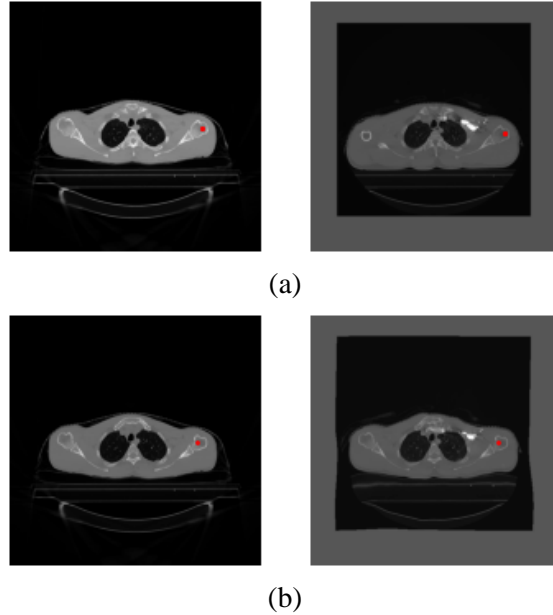


Figure 2: A pair of matched points in the same slice of the reference image and the resulting image of (a) the rigid and (b) the deformable registration.

From the mutual information values in Table I, it is also possible to verify that the deformable registration presented a better performance since the information shared between the reference image and the resulting image of the rigid registration was smaller than that shared between the reference image and the resulting image of the deformable registration.

4. Conclusions

As expected, the deformable registration presented more accurate results when compared to the rigid registration, exactly because the rigid transformation of an image has limitations in the alignment between the images, while the deformable one is capable of determining a voxel-to-voxel transformation in the image. However, even the results of the deformable registration were not completely satisfactory, the ideal situation would be to obtain a mean error around or below the maximum voxel dimension.

Such registration results, obtained with reference points on the images, vary according to the anatomy of each patient, as well as the module and software that are used for registration in each clinic/hospital. Thus, quantitative analysis for image registration quality assurance becomes extremely important in radiation therapy, an area that increasingly aims to optimize dose delivery to the tumor and spare healthy tissues and organs.

Acknowledgments

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