Constrained registration of 3D MR and cone beam CT of abdominal organs

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Abstract

This paper aims at performing an automatic co-registration of 3D MR and a 3D cone-beam CT of the abdomen with the help of manually indicating a region of interest. Image registration in the abdominal region is challenging due to the elastic nature of non rigid structures. This problem is addressed by manually indicating the region of interest and allows the registration to concentrate only in this region. Normalized Mutual Information is used as similarity measure and the Powell method as Optimization method. A B-spline kernel is used to smooth the data, which is an additional examined feature, leading the method towards more robustness. The results of the automatic registration algorithm are presented and discussed for a number of clinical datasets.

1 Introduction

Image registration is an important technique in medical image processing. It is a process for aligning two images collected at different times or using different imaging modalities or from different subjects. One of the images is referred to as the reference and the other image is referred to as floating. The spatial transformation that is needed to align the floating image with the reference image is the outcome of an image registration algorithm. It has wide spread applications in a variety of fields, such as computer vision, pattern recognition and medical image analysis, etc. The image registration in medical image analysis targets diagnosis and treatment which also involves interventional surgery [13, 14, 15]. The data taken from the same subject at different times is often for change detection like tumor monitoring. Few other applications are motion correction, spatial normalization, etc.

Image registration technique can be classified into “rigid” and “non rigid” image registration. In general for the organs like brain, bones etc. transformations applied are mostly rigid. Such transforms are only allowed to translate or rotate. Sometimes, affine transforms are applied which also allowed to scale and skew along with the translation and rotations. For organs with more elastic nature like lungs, heart etc. local transformations are required to register the images. In such cases, algorithms which apply local transformations are required. These techniques are considered as non-rigid registration techniques, also know as deformable, non-linear or elastic registration. In this paper we have applied rigid transformations within a constrained region of interest targeting abdominal organs. We assume rigid registration within a constrained region can be used when the local deformation within the region of interest is limited [21].

2 Constrained Registration State of Art

Non rigid registration is used to model either organs with more elastic nature or the organs situated in the region where there is less stability regarding the position of the organ. A promising direction appears to be adding physiologically meaningful constraints. Such constraints can be rigidity of bones, incorporation of anatomical landmarks, etc.

Several methods to constrain deformations for the non-rigid registration have discussed in the literature. Rohlfing et al [9], proposed a global Jacobian constraint. Loeckx et al [4], extended Rueckert et al's [11], smoothness constraint to the required regions. After that, Staring et al [17], proposed a composite constraints which includes linearity constraint, orthonormality constraint and properness constraint, Heinrich et al [3], presented a optical flow constraint. Few methods are proposed to apply rigid constraints in non-rigid registration during regularization like, Staring et al [17] using B-splines, Ruan et al [10], regularizing the Jacobian in rigid regions, Haber et al [1], using Lagrangian approach of transformation model. Zhang et al [5], proposed a registration technique making use of automatic segmentation and constrained B-spline based free-form deformations ,which are mainly used for data analysis in thoracic and abdominal applications.

Incorporating constraints is challenging. Constraints can be added either as "hard"-constraints (i.e. the constraints have to be fulfilled exactly) or as "soft"-constraints (i.e. the constraints hold only approximately). "Soft"- constraints lead to a penalty approach. Applying constraints reduces the level of non uniqueness and thus generates more reliable transformations, thereby improving their robustness and accuracy [6]. The primary clinical application of the work presented in this paper concerns minimally invasive treatment. During this application, the physician might be interested to concentrate either on a particular region of interest or an organ. This can be done by a ROI-based registration. Few feature-constrained nonrigid registration methods are proposed, with an intensity similarity measure along with smoothness constraints (Han et al [2],), or with inequality constraints (Papenberg et al [7],). Yan et al [22], proposed a framework which incorporates region constraints by assigning distinct labels to each region. Yi et al [23], concluded that registration using an ROI restricted to the anatomical region of diagnostic interest provides higher accuracy than using a larger ROI. Schäfer et al [16], evaluated the different registration results using a pharmacokinetic model function for local region of interest registration of small lesions in dynamic contrast-enhanced MRI.

3 Approach

The specific features of the registration algorithm explained in this article are:

1. ***Normalized Mutual information:*** The similarity measure we use in this paper is based on Normalized mutual information. The goal of the registration of two images A and B is to obtain the transformation T that maximizes the similarity between A and T(B). Usually, mutual information is an effective similarity measure used for multimodality image registration. Normalized mutual information is largely independent of the overlap area and therefore it is suited for a region constrained registration [18].

2. ***POWELL Method***: The optimization method we use in this paper is the POWELL method. The objective of the POWELL method is to find the minimum nearest to the starting point. Its principal advantage is that it is a robust direction-set method. A set of directions (e.g., unit vectors) are defined; the method moves along one direction until a minimum is reached, then from there moves along the next direction until a minimum is reached, and so on. This method is further discussed in [8].

3. ***B-Spline kernel:*** In computer graphics, B-splines are commonly used for interpolations or approximation curves and surfaces [19, 12]. In this article we

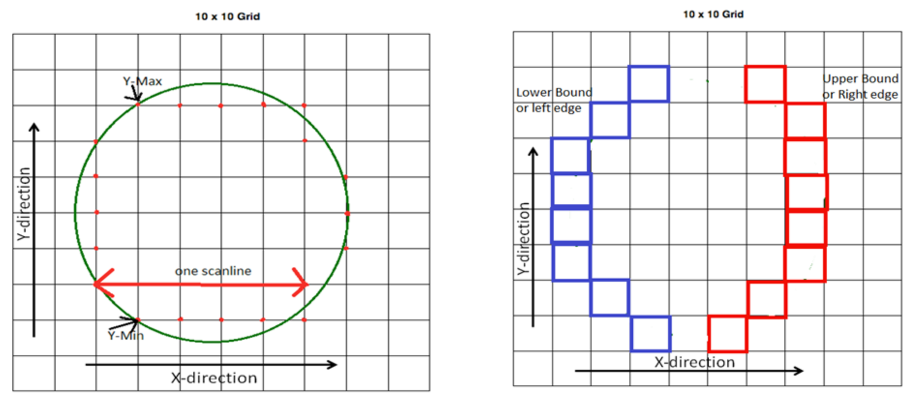

Figure 1: The scanline algorithm

use them for a smoothening filter. In this approach, the volumetric data are sampled on the regular, uniform and rectilinear grid. A 3×3×3 kernel with these specific B-spline coefficients runs all over the image and the data interpolation takes place. The kernel does not fits in the boundary voxels. So, those voxels are replaced with the same grey values without smoothening. The smoothing with this B-spline kernel is applied for both the reference and floating images without considering any ROI. The whole image is smoothened.

4. ***Constrained registration by selecting ROI:*** The main aim of this article is to evaluate the results for a constrained registration for a particular region of interest. A region of interest is selected manually and the shape of the region should be a convex polygon. We used the scan line algorithm in order to render the volume inside the ROI. Scanline algorithms operate on a frame buffer scanline by scanline by managing a list of currently active edges and processing the pixels between the start and end of the polygons. Instead of operating on single samples, scanline rasterization operates on scanlines by computing the interval of covered samples per scanline. When a ROI is selected, the boundary points are captured (Fig. 1 Left). Using the bubble sort method, the lower bound and upper bound in every line per slice are noted. This means that the lower bound and upper bound are the lowest and highest x-coordinate for every y-position between Ymin and Ymax for every slice in the z-direction (Fig. 1 Right). We assign zeros to all the voxels of the image outside scanline, which are initially set with their corresponding grey values [20].

4 Results and Discussions

The data used here are obtained with MRI (Philips Healthcare, Best, the Netherlands) and conebeam CT (XperCT, Philips Healthcare, Best, the Netherlands) from three subjects in the abdominal region. The registration applied is always intra-subject. It is mostly between inter-modalities as mentioned MRI and XperCT and also between XperCT and XperCT for all the three subjects. By, considering combinations of images with different image qualities from MRI and XperCT as reference and floating images, the advantages and disadvantages of this approach are observed. XperCT images are used to observe intramodality registration. The property of the XperCT image pairs is that they are taken at two different timings and with different image quality. The details of the XperCT and MRI images used as reference and floating images from three subjects are specified in Table 1.

Table 1: Details of the XperCT and MRI images of the three subjects

Subject name		Modality	Volume dimensions	Voxel size(mm)	Image quality
HMMB	Mb1	XperCT	[256,198,256]	[0.98,0.98,0.98]	Fine
	Mb2	XperCT	[256,198,256]	[1.38,1.38,1.38]	Medium
	Mb3	MRI	[290,320,30]	[1.25,1.25,6.50]	Coarse
	Mb4	MRI	[320,260,30]	[1.13,1.13,6.00]	Coarse
	Mb5	MRI	[320,260,72]	[1.19,1.19,3.00]	Fine
	Mb6	MRI	[320,240,72]	[1.25,1.25,3.00]	Fine
HMSP	Sp1	XperCT	[256,198,256]	[0.98,0.98,0.98]	Fine
	Sp2	XperCT	[256,198,256]	[1.38,1.38,1.38]	Medium
	Sp3	MRI	[320,250,56]	[1.19,1.19,3.00]	Fine
HMJJ	Jj1	XperCT	[256,198,256]	[0.98,0.98,0.98]	Fine
	Jj2	XperCT	[256,198,256]	[1.38,1.38,1.38]	Medium
	Jj3	XperCT	[256,198,256]	[0.98,0.98,0.98]	Fine
	Jj4	MRI	[320,240,72]	[1.25,1.25,3.00]	Fine

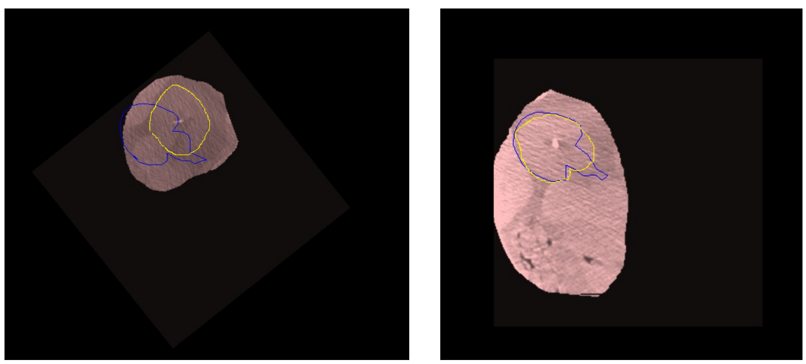

Figure 2: Left: Mismatch because of small selected region. The blue line indicates the outline of the organ in the reference image and the yellow line the outline in the floating image. Right: Good match because of an increase in the size of the region of interest

The algorithm discussed in this paper implements constrained registration with a ROI and B-spline smoothing of the data. As a result, there are four categories which are considered:

- Ca1: with a ROI and smoothing (with both).
- Ca2: with a ROI and without smoothing (only ROI).
- Ca3: without a ROI and with smoothing (only smoothing).
- Ca4: without both ROI and smoothing (without both).

When a registration is performed by selecting an ROI, one basic requirement will concern the size of the ROI. If the selected region is too small, then the method does not work. The reason for this drawback might be that the common data between the images is too limited for the registration. The resulting mismatch connected to the small selected region can be observed in Fig. 2 Left and a good match after the selected region was increased can be observed in Fig. 2 Right.

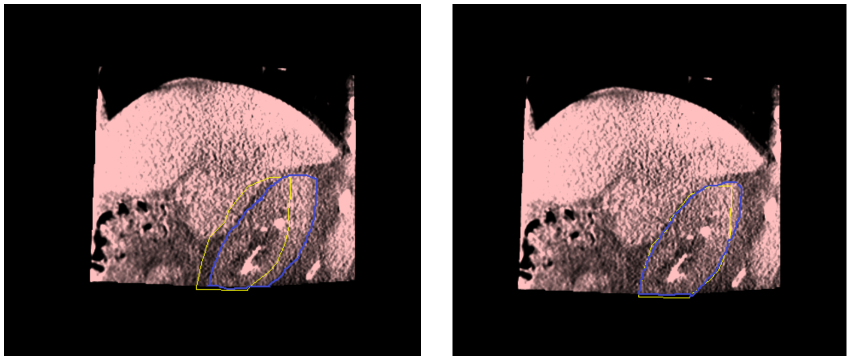

Figure 3: Left: Registering without manual initialization leads to getting stuck in a local optimum. Right: Manual initialization helps the automatic registration to find the global optimum.

Table 2: Results for the different combinations of XperCT with MRI of the three subjects

Subject	XA/MR	Ca1	Ca2	Ca3	Ca4	Image quality
HMMB	Mb1/Mb3	+	−	−	−	Coarse (r)
	Mb1/Mb4	−	−	+	+	Coarse (r)
	Mb1/Mb5	++	+	+	+	Fine
	Mb1/Mb6	+	+	+	+	Fine
HMSP	Sp1/Sp3	+	++	+	−	Fine
	Sp2/Sp3	++	−	+	−	Medium (f)
HMJJ	Jj1/Jj4	++	+	++	+	Fine
	Jj2/Jj4	+	−	−	−	Medium (f)
	Jj3/Jj4	++	++	++	++	Fine

Our automatic registration is preceded by a coarse manual initialization. We have observed that a proper manual initialization prevents the automatic registration from getting stuck in a local optimum, as can seen by comparing Fig. 3 Left and Right.

An outline is drawn along the boundary conditions of the organ in both the images which is used only to verify the results. This is considered as the visual proof of a bad or perfect registration basing on the alignment of the boundary outlines of both the images. The observed results after image registration using the different conditions are presented below in Table 2 and Table 3.

The following points are observed from the table:

1. The registration yields the best results with images of good resolution and the absence of local deformations within the ROI, as is shown in Fig. 4.
2. Poor resolution or local deformations can lead to suboptimal registration results, as is shown in Fig. 5.
3. The problem of poor resolution can be reduced with the help of B-spline smoothing, which has been observed for some images with poor resolution with smoothing was observed.
4. Region constraint and smoothing have been found to improve the registration results.
5. Table 3 shows that this approach works well for intra-modality like XperCT to XperCT registration. A possible drawback might be a lower resolution. And

Table 3: Results for the different combinations of XperCT with XperCT of two subjects

Subject	XA/XA	Ca1	Ca2	Ca3	Ca4	Image quality
HMMB	Mb1/Mb2	++	+	+	−	Medium (f)
HMJJ	JJ1/Jj2	++	++	++	++	Medium (f)
	Jj2/Jj3	++	+	−	−	Medium (r)
	Jj3/Jj2	++	+	++	++	Medium (f)

Where, − bad, + good with some defects, ++ Perfect.

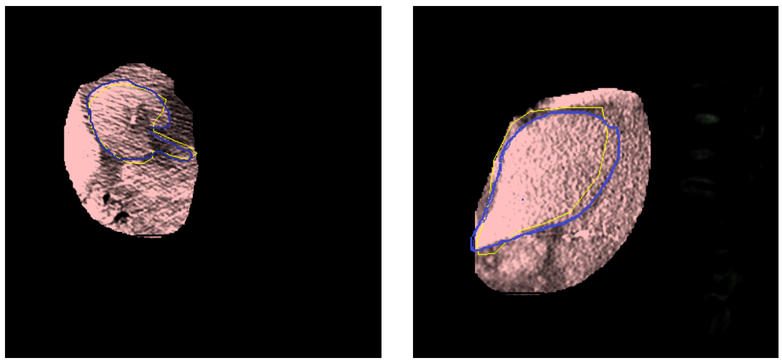

Figure 4: Left: Perfect registration of a kidney between high resolution MRI and XperCT images. Right: Perfect registration of a liver between high resolution XperCT and XperCT images.

in few images observed there was less information in common, which leads to failure.

5 Conclusion

In this paper, we presented a region constrained approach in the framework of image registration, especially in the abdominal region. The images are registered using not only voxel intensities but also constrained to a specific region of interest, which can overcome the negative impact of other parts of the abdomen. A B-spline smoothing kernel is also used in order to smooth the data, which is useful to overcome the problem of poor resolution. From the discussions, this region constrained registration is shown to be feasible for the images with good resolution and no local deformation within the ROI. The only precaution has to be taken is size of the ROI and sufficiently accurate manual initialization.

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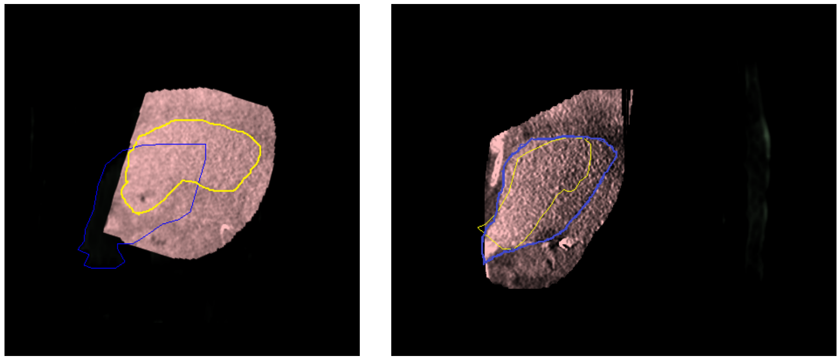

Figure 5: Left: Bad registration of a liver between MRI and XperCT images due to poor resolution. Right: Local deformations within the ROI lead to sub-optimal registration results.

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