Direct inverse deformation field approach to pelvic-area symmetric image registration

Bartlomiej W. Papiez
bwpapiez@uclan.ac.uk
Bogdan J. Matuszewski
bmatuszewski1@uclan.ac.uk

ADSIP Research Centre
University of Central Lancashire
Preston, UK

Abstract

This paper presents a novel technique for a consistent symmetric deformable image registration based on an accurate method for a direct inversion of a large motion model deformation field. The proposed image registration algorithm maintains one-to-one mapping between registered images by symmetrically warping them to another image. This makes the final estimation of forward and backward deformation fields anatomically plausible and applicable to adaptive prostate radiotherapy. The quantitative validation of the method is performed on magnetic resonance data obtained for pelvis area. The experiments demonstrate the improved robustness in terms of inverse consistency error and estimation accuracy of prostate position in comparison to the previously proposed methods.

1 Introduction

Image registration is a fundamental task in medical image processing aiming at an optimal, in some sense, estimation of spatial transformation aligning two or more images. As the image registration is an ill-posed problem it needs to be regularised by introducing additional *a priori* information to the estimation process [4]. In the classical formulation of a non-parametric image registration, methods based on elastic, fluid, diffusive deformable models [5] are commonly used to enforce a globally smooth dense deformation field. Although those methods have been shown to be fast and accurate, they have a drawback when used in clinical applications as they do not explicitly preserve organs' topology. To maintain the neighbourhood relationship and avoid anatomically incorrect deformations, the inverse consistency error (ICE) has been introduced. In the earliest work on minimising the ICE during image registration, an algorithm jointly estimating a forward and a backward transformation was proposed [2]. A similar idea of simultaneously reducing the ambiguous correspondence between the forward and the backward transformation but established via a variational framework and not limited to mono-modal images was presented in [8]. Recently a diffeomorphic formulation of the image registration was proposed [1, 6] as an efficient way of preventing transformation folding. All of those methods have been validated on MRI and CT images of a brain with relatively small deformations, meanwhile the adaptive radiotherapy (ART) of prostate cancer requires to cope with significant changes of bladder and rectum shape and size. To overcome this problem, a symmetric warping between two images was introduced

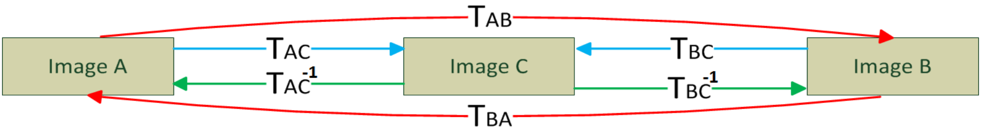

Figure 1: Symmetric image registration scheme

by registering these images to an intermediate image [3, 7]. These methods require though an explicit calculation of the inverse deformation fields.

The method proposed in this paper extends the approach presented in [7] by directly inverting deformation field in each iteration. This allows the alleviation of constraints imposed on the maximum magnitude of the deformation field update in every iteration of the algorithm. Finally, the proposed registration scheme is compared against the algorithm proposed in [7], demonstrating improvement of the ICE and the accuracy of the prostate position estimate.

2 Symmetric Image Registration

The consistent symmetric image registration is defined here for mono-modal images with A representing a fixed (reference) image and B a moving image. Corresponding deformation (displacement) fields at any spatial position are defined as: $\vec{x}$: $T_{AC} = \vec{x} + \vec{u}(\vec{x})$ and $T_{BC} = \vec{x} + \vec{v}(\vec{x})$ warping respectively image A and image B to an intermediate image C. Mathematically it can be stated as an optimisation problem:

$$\arg \min_{u,v} \left(Sim(A \circ u, B \circ v) + \alpha_u Reg(u) + \alpha_v Reg(v)\right) \tag{1}$$

where: Sim is a chosen similarity measure between images (*e.g.* the Sum of Squared Differences [5]), Reg is a regularisation term, and α_u, α_v are regularisation weights. To solve this problem, the Demon-like force established in an iterative optimisation framework [6, 7] was chosen:

$$du_{i+1} = \frac{(A_i - B_i)(\nabla A_i + \nabla B_i)}{\|\nabla A_i + \nabla B_i\|^2 + (A_i - B_i)^2} \tag{2}$$

where: A_i is warped image A using estimated deformation field u_i; B_i is warped image B using estimated deformation field v_i; ∇A_i is gradient of image A_i; ∇B_i is gradient of image B_i; i is an index of the current iteration. The results of this registration towards the intermediate image: T_{AC} and T_{BC} need to be inverted and the final transformations T_{AB} and T_{BA} are the compositions of T_{AC} and T_{BC} and their inverses T_{AC}^{-1} and T_{BC}^{-1}: $T_{AB} = T_{AC} \circ T_{BC}^{-1}$ and $T_{BA} = T_{BC} \circ T_{AC}^{-1}$. The overall scheme of this registration process is illustrated in Fig. 1.

2.1 Small-step multiple pass approach

In a *small-step multiple pass approach* originally proposed in [7], it is assumed that:

$$u_{i+1} = G_e * \left(u_i \circ \left(G_f * (du_i)\right)\right) \qquad v_{i+1} = G_e * \left(v_i \circ \left(G_f * (-du_i)\right)\right) \tag{3}$$

where: G_e* and G_f* represent Gaussian kernel convolutions which operate on updated displacement fields u and v and updated velocity field du respectively. This assumption simplifies significantly the estimation of the deformation fields but it holds only for small updates. The Demon-like force does not guarantee the small-step update and therefore the explicit procedure, limiting the deformation magnitude is applied when the estimated update is greater than 0.4 voxel size. However, image registration in the ART requires not only to be accurate but also fast and the update magnitude limiting procedure contradicts these requirements. Additionally it needs to be checked how good this approximation of the inverse update is in practise.

2.2 Direct inverse deformation field approach

The proposed method builds on the previous approach by directly inverting update of the deformation field in each iteration. The directly inverted deformation field is obtained by finding zero of a misalignment function $\vec{f}(\vec{x})$ defined for an arbitrary point $\vec{y}$ form the range of transformation $\vec{T}_{input}$: $\vec{f}(\vec{x}) = \vec{y} - \vec{T}_{input}(\vec{x})$. It can be shown using Taylor expansion, that $\vec{f}(\vec{x}+\vec{dx}) \approx \vec{f}(\vec{x}) + J(\vec{f}(\vec{x}))\vec{dx}$. The estimated $\vec{x}$ can be found in an iterative manner; for iteration i, assuming that $\vec{f}(\vec{x}_i + \vec{dx}_i) = 0$, $\vec{x}_{i+1}$ is given by $\vec{x}_{i+1} = \vec{x}_i + \vec{dx}_i$ where $\vec{dx}_i$ is calculated by solving a set of linear equations: $J(\vec{f}(\vec{x}) + \beta I)\vec{dx} = \vec{f}(\vec{x})$. Here $J(\vec{f}(\vec{x}))$ is the Jacobian of $\vec{f}(\vec{x})$. The βI, where I is the identity matrix and β is a non-negative number is used to regularise the set of equations when the condition number of $J(\vec{f}(\vec{x}))$ is above a given threshold, otherwise β is set to zero. This method of inverting deformation field can be seen as a modification of the method proposed in [2], enabling to invert more accurately large deformations. Finally, the corresponding update scheme is as follows:

$$u_{i+1} = G_e * \left(u_i \circ \left(G_f * (du_i)\right)\right) \quad v_{i+1} = G_e * \left(v_i \circ \left(G_f * \left(du_i^{-1}\right)\right)\right) \tag{4}$$

This scheme in contrast to Eq. 3 (compare formulas for updating v_{i+1}) uses the direct inverse update of the deformation which does not suffer from the limitations of the *small-step multiple pass approach*.

3 Experimental results

To evaluate the accuracy and robustness of the proposed approach, multiple pelvic MRI scans of the same subject were used. For quantitative evaluation, the previously proposed framework [1] was compared against the proposed method using the inverse consistency error (ICE) measure defined as:

$$ICE(T_{AB}, T_{BA})(\vec{x}) = \frac{1}{2}(\|(\vec{x} - (T_{AB} \circ T_{BA})(\vec{x}))\| + \|(\vec{x} - (T_{BA} \circ T_{AB})(\vec{x}))\|) \tag{5}$$

and maximal ICE ($maxICE$):

$$maxICE(T_{AB}, T_{BA})(\vec{x}) = max(\|(\vec{x} - (T_{AB} \circ T_{BA})(\vec{x}))\|, \|(\vec{x} - (T_{BA} \circ T_{AB})(\vec{x}))\|) \tag{6}$$

The relative overlap (RO) between prostate segmented in the reference image, P_{ref}, and in the warped moving image after registration, P_{warp}, was used to evaluate the registration performance in terms of the prostate position. The RO has been defined as:

$$RO(P_{ref}, P_{warp}) = \frac{2 * numberOfVoxels(P_{ref} \cap P_{warp})}{numberOfVoxels(P_{ref} \cup P_{warp})} \tag{7}$$

The data set consists of 5 volumes of $320x240x30$ voxels with voxel size of $1.0x1.0x3.0mm$. In each scan, the data exhibit significant changes of bladder size and shape. A sample of the

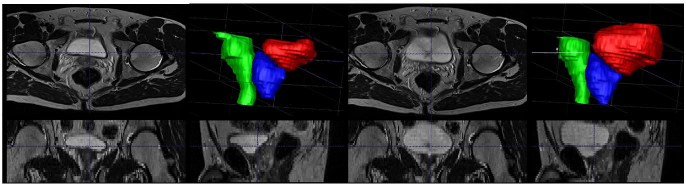

Figure 2: Example of the data used in the experiments: volume labelled as *Image 3*, selected as the reference image (left); volume labelled as *Image 5* (right). Segmented bladder, rectum and prostate are shown in red, green and blue respectively.

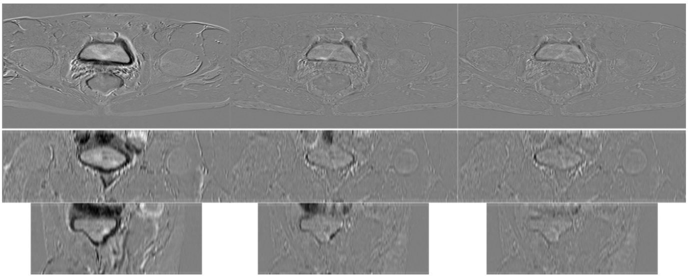

Figure 3: Axial (top), coronal (middle) and sagittal (bottom) views of the difference between reference image and moving image before registration (left), after registration using Yang's method (middle), and the proposed method (right).

data is shown in Fig. 2. Image which is labelled as *Image 3* was chosen as a reference image for all experiments.

The dispersion of 0.5 and 1.0 was used for G_e and G_f smoothing Gaussian kernels respectively; the maximal number of iteration was set to 50 and the multi-linear interpolation method was implemented to estimate non-grid values of images and deformation fields.

The results presented in Tab. 1 show that the proposed framework produces smaller *ICE* and *maxICE* than previously proposed method, especially when a significant deformation needs to estimated (*e.g.Image 4* and *Image 5*). The difference between images before and after registration is shown in Fig. 3. The proposed method is also seen as more robust. This is mainly due to applied method for the direct calculation of the inverse deformation field. The proposed method performs better when compared to Yang's method [7] in terms of prostate position accuracy, as in all the cases the proposed method achieve greater values of *RO* as illustrated in Fig. 4.

4 Summary

Registration of pelvic area images is challenging due to possible significant shape and size changes of bladder and rectum. To provide an accurate method for estimation of the prostate position, the consistent symmetric image registration framework based on the direct inversion procedure is proposed in this paper. The quantitative validation preformed on real MRI data shows that proposed modifications of the previously reported algorithms resulted in

	ICE (maxICE)							
	Image 1		Image 2		Image 4		Image 5	
Yang's [7]	0.27	(8.08)	0.14	(5.07)	0.14	(4.96)	0.34	(10.8)
The proposed	0.04	(1.68)	0.04	(1.30)	0.03	(0.96)	0.05	(3.84)

Table 1: *ICE* and *maxICE* (in brackets) calculated for deformation field estimated using Yang's framework [7] and the proposed framework.

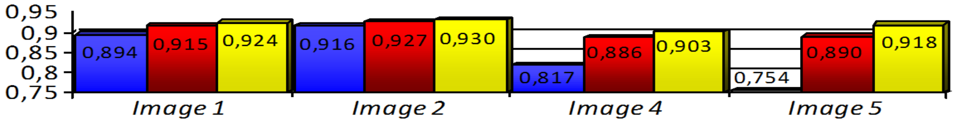

Figure 4: RO for segmented prostate before registration (blue), after registration using Yang's method [7] (red), and after registration using the proposed method (yellow).

the somewhat improved prostate *RO* measure and the significant reduction of the *ICE* and *maxICE* measures.

Acknowledgement

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