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Elastic Registration Based on Particle Filter in Radiotherapy Images with Brain Deformations

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***Abstract*—This paper presents the evaluation of the accuracy of an elastic registration algorithm, based on the particle filter and an optical flow process. The algorithm is applied in brain CT and MRI simulated image datasets, and MRI images from a real clinical radiotherapy case. To validate registration accuracy, standard indices for registration accuracy assessment were calculated: the dice similarity coefficient (DICE), the average symmetric distance (ASD) and the maximal distance between pixels (Dmax). The results showed that this registration process has good accuracy, both qualitatively and quantitatively, suggesting that this method may be considered as a good new option for radiotherapy applications like patient's follow up treatment.**

***Index Terms*—Elastic image registration, particle filter, optical flow, simulation datasets, radiotherapy real clinical case.**

I. Introduction

ONE important subject in medical image analysis is image registration [1], which consists in a spatial remapping of one image to another to obtain a voxel by voxel correspondence of the same anatomical structures in the two images. In fact, image registration is useful to recover organ deformations during the evolution of certain diseases or the treatment of them. In particular, in radiotherapy, it allows the estimation of strains that can be caused by increase or reduction of tumors treated with radiation, or by side effects such as weight loss or increase / reduction of the healthy organs surrounding the tumor [2].

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In the last years, image registration has been approached with rigid and non-rigid techniques. Rigid registration methods assume that the same global transformation is applied to each image pixel, thus reducing the problem to find only the parameters which describe the global transformation. However, these methods present serious drawbacks when one of the images shows complex deformations with respect to the other one. On the other hand, non-rigid or "elastic" registration methods estimate a transformation for each pixel, incorporating only weaker smoothness assumptions in order to make the problem well-posed. Elastic methods are more general than the rigid ones but also more computationally demanding, and difficult to implement and calibrate [3].

Recently, a new approach has been proposed for rigid registration, based on the Particle Filter (PF), an algorithm commonly used for parameter estimation in dynamical systems [4]. In this method, an iterative stochastic search is performed using a Monte Carlo model. This new approach based on PF has been also adapted to non rigid image registration cases, by incorporating an optical flow approximation [5]. This iterative process is reported to be easy to implement and powerful enough to achieve complex non-rigid registrations; however, before its application on a real clinical context, validation of the algorithm accuracy should be performed.

In this work, the evaluation of PF elastic registration accuracy is carried out in the case of 2D images, using simulated data. Its application to a real clinical case is also shown.

II. Methods

A. Simulated Image Datasets

CT and MRI studies of two patients with cerebral tumor treated with macroscopically total resection were selected, in which the presence of deformations in the head and neck tract caused by tumors were evident. These patients underwent pre-operative diagnostic, surgical resection and radiotherapy treatment at the San Raffaele Hospital in Milan, Italy.

CT and MR 2D images of three different sections of the head were selected to study different morphological structures; each image was deformed in a controlled way (5 deformations per image).

The controlled deformations were obtained using the Moving Least Squares (MLS) algorithm [6], which is a deformation technique that allows to compute a map f:R2→R2 from the transformation of a set of N pivot points "p" in new positions "q". For the simulated deformations we put 6 pivot points initially placed at 60, 120, 180, 240, 300 and 360 degrees around the outer structure of each image. Subsequently, these pivot points were moved, randomly, ±5–10 pixels, both in x-axis and y-axis, to generate the corresponding warps.

Two simulated datasets were thus obtained:

1. CT simulated dataset; original CT images with their corresponding simulated deformations.
2. MRI simulated dataset; original MRI images with their corresponding simulated deformations.

It should be emphasized that for evaluation purposes, simulation was intended to study deformations even exaggerated or impossible to find in actual radiotherapy clinical cases.

B. Clinical Images

A real clinical case was considered using MRI images acquired before (MRI-Pre) and after (MRI-Post) a radiotherapy treatment, where it is possible to observe deformations of brain structures, in the axial plane, due to the tumor shrinkage as a result of the treatment. In this case the proposed method was used to remap post-treatment imaging back to pre-treatment images in order to estimate brain structures changes occurred during treatment.

A slice by slice correspondence between MRI-Pre and MRI-Post was obtained, using the rigid registration software available on the radiotherapy plan computer.

C. Parametric Particle Filter

The Particle Filter (PF) is a method based on Bayesian approach that uses a Montecarlo algorithm to estimate a probability density function (pdf) [4]. The goal of the PF is to obtain a posterior pdf at time k, through a set of test points θ_k^j (particles: in this case the parameters of an affine transformation) with associated weights $\{\theta_k^j, W_k^j\}_{j=1}^{Ns}$, such that $\sum_{j=1}^{Ns} W_k^j = 1$, and N_S the particle number.

The PF algorithm is an iterative process composed of two stages:

1. *Prediction stage*: each particle is modified by a random walk pattern ($\theta_k = \theta_{k-1} + v_{k-1}$, where v_{k-1} represent i.i.d. noise samples), through a recursive propagation of the particles at time k. A resampling process is needed in order to select only the best particles to be propagated, solving the Degeneracy Problem (particles with negligible weights).
2. *Update stage*: the weights are recalculated according to the measurements z_k, using the likelihood function $P(z_k|\theta_k)$, defined by the measurement model in order to obtain representatives samples of $P(\theta_k|z_k)$ [5].

The algorithm uses mutual information (MI) as likelihood measurement in the image registration process, thus it is possible to define the output measurement z_k as:

$$z_k = MI(I_T(x,y), I_s(T_{\theta_k}(x,y))) + w_k \qquad (1)$$

where I_T and I_S are the target an source images, $T_\theta(.)$ is the geometric (affine) transformation and w_k represent i.i.d. noise samples; if I_S is the result of a bijective intensity mapping for I_T, then, by using the property of MI [5], and the entropy H(.) of the I_S, it is possible to define $P(z|\theta)$ as likelihood metric [7]:

$$P(z|\theta) = \frac{1}{\sigma\sqrt{2\pi}} exp\left\{-\frac{[H(I_T(C)) - MI(I_T(C), I_S(T_\theta(C)))]^2}{2\sigma^2}\right\}, \qquad (2)$$

for a given measurement noise variance $\sigma^2>0$ and a set of m equispaced pixels $C = \{(x_i, y_i); i = 1, \ldots, m\}$, in both images. Note that (2) reaches its maximum when $I_S(C) = F(I_T(T_\theta(C)))$, where F(.) denotes an injective intensity mapping.

D. Elastic Registration using PF and optical flow

For the elastic registration the key idea lies in a two step iterative algorithm; first, the global affine registration between both images using the PF approach is computed; second, the transformation is locally refined for each pixel using an optical flow approximation [5]. The aligned candidate image, obtained at each iteration, is used as the input candidate image in the following iteration until convergence is reached. An important advantage on this method is that only a few control parameters are required and these parameters are robust with respect to the images to be registered. In the case of affine registration, the parameters are the number of particles and the number of iterations, while, for optical flow, estimation requires taking into account the number of iterations and the value of a regularization factor λ, that controls the smoothness of the resulting flow field. In this work for all the registrations we used 300 particles and 200 iterations for calculating the affine transformation, and 50 iterations with λ=5000 for the computation of optical flow. All these experiments were performed on a PC running at 3.06 GHz.

E. Registration accuracy on simulated data

The algorithm was applied to the simulated datasets, using the parameters mentioned above; the mean registration time was 45 seconds.

To validate registration accuracy, in both internal and external brain structures, segmentation of some structures of interest were performed: in each simulated study an expert in radiological images interactively drew the brain contour (including the main sulci), the lateral cerebral ventricles contours (divided in top and bottom left/right ventricles) and the tumor boundary using MIPAV software [8].

From these data, differences in structures between original and deformed images (pre registration) and between original and post registration images were calculated using standard indices usually adopted for registration accuracy assessment [9]: the dice similarity coefficient (DICE), the average symmetric distance (ASD) and the maximal distance between pixels (Dmax).

The value of DICE ranges from 0, indicating no spatial overlap between two sets of binary segmentation results, to 1, indicating complete overlap. ASD is based on the contour pixels of two segmentations A and B. For each contour pixel of B, the Euclidean distance to the closest surface pixel of A is calculated and stored. In order to provide symmetry, the same process is applied from contour pixel of A to B. The ASD is then defined as the average of all stored distances, which is 0 for a perfect segmentation. The Dmax index calculates the maximum distance between the analyzed overlapped contours, where zero means a perfect overlap.

F. Clinical Case Registration

The algorithm was applied to the clinical images, using the same parameters set for the simulated datasets. For these images the registration time was 46 seconds.

Qualitative analysis of the algorithm performance was carried out by an expert physician, taking into account the misalignment recovery of particular structures (right ventricle and tumor). Quantitative analysis was performed using the same criterion applied in simulated data.

III. Results and discussion

A. Simulated data

Figure 1 shows an example of the results found using images with simulated deformations in both MRI (row a) and CT (row b) images. In this figure, we can see (by columns) the original images, the deformed images and their respective registration (resulting image). It could be observed that the PF has made an acceptable registration between images. Qualitatively, registered images look very similar to the original ones, regardless of the degree of the applied strain. The good recovery is particularly evident by looking at the contours of the brain, the brain ventricles and the tumor (white area at the top left).

Complementing figure 1, Table I shows the results of calculated indices DICE, Dmax and ASD in CT-CT and MR-MR registrations. Values were calculated for pre and post registrations, corresponding to values of the pairs original-deformed images and original-registered images respectively, of the 5 strains applied (Def 1, Def 2, Def 3, Def 4 and Def 5). It also presents the mean, standard deviation and median values for each pre and post indices.

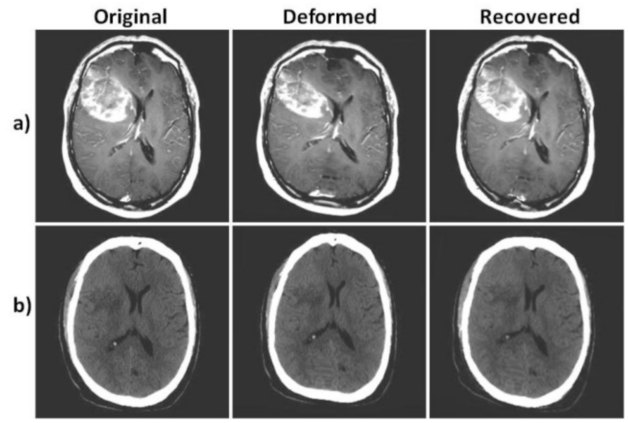

Fig. 1. a) MRI images, b) CT images.

The values of pre and post ASD were about 2.70 ± 0.59 mm and 0.80 ± 0.41 mm for CT, 2.68 ± 0.43 mm and 0.92 ± 0.60 mm for MR, while Dmax values decreased from 7.76 ± 1.68 mm to 3.46 ± 1.23 mm for CT and 8.47 ±1.57 mm to 3.80 ± 1.17 mm in MR respectively. Taking into account that the pixel size of these images is 0.819 mm, these results show that the uncertainties in the alignment of the structures were reduced to values comparable to the pixel size. For DICE index results show a considerable improvement since the found values increased from 0.55 ± 0.28 for CT and 0.48 ± 0.07 for RM, to 0.86 ± 0.19 and 0.85 ± 0.10 respectively, indicating that the overlap of the contours had an improvement from 50% to 85%.

TABLE I
Registration Accuracy in Simulated Data.
Each deformation value (Def) is the mean value of the brain and ventricles structures for each simulation.

CT-CT

	ASD(mm)		Dmax(mm)		DICE	
	pre	post	pre	post	pre	post
Def 1	2,31	0,46	6,06	1,99	0,65	0,93
Def 2	3,03	0,45	8,16	2,95	0,45	0,93
Def 3	2,55	0,81	8,19	3,69	0,58	0,86
Def 4	2,08	0,85	6,22	3,34	0,64	0,84
Def 5	3,55	1,45	10,16	5,34	0,44	0,72
mean	**2,70**	**0,80**	**7,76**	**3,46**	**0,55**	**0,86**
SD	**0,59**	**0,41**	**1,68**	**1,23**	**0,10**	**0,08**
median	**2,55**	**0,81**	**8,16**	**3,34**	**0,58**	**0,86**

MR-MR

	ASD(mm)		Dmax(mm)		DICE	
	pre	post	pre	post	pre	post
Def 1	2,38	0,40	6,72	2,92	0,55	0,93
Def 2	2,93	0,46	9,58	2,33	0,39	0,92
Def 3	2,59	1,45	8,68	4,78	0,49	0,76
Def 4	2,21	0,61	7,04	3,89	0,54	0,91
Def 5	3,29	1,68	10,32	5,06	0,42	0,72
mean	**2,68**	**0,92**	**8,47**	**3,80**	**0,48**	**0,85**
SD	**0,43**	**0,60**	**1,57**	**1,17**	**0,07**	**0,10**
median	**2,59**	**0,61**	**8,68**	**3,89**	**0,49**	**0,91**

B. Clinical Images

Figure 2 shows the result for the real clinical case, in which the right hemisphere of the brain is affected by the tumor. In this figure pre-treatment, post-treatment and recovered images are presented.

To analyze the efficiency of the registration, arrows were placed pointing the most deformed structures (cerebral ventricles and tumor). Comparing the post-treatment image with respect to the pre-treatment one, deformations on the brain ventricles structures of the right hemisphere are observed; also a shrinking of the tumor is present. Analyzing the recovered image and the pre treatment image, it is possible to appreciate that the shape of the ventricles is properly recovered, maintaining the tumor's shrinkage. Table II presents the results obtained with ASD, Dmax and DICE indexes in this particular case, confirming qualitatively the efficiency of the proposed registration method in real clinical data. These results suggest that the methodology proposed in this work may be helpful for following up studies in radiotherapy thanks to its good performance and accuracy.

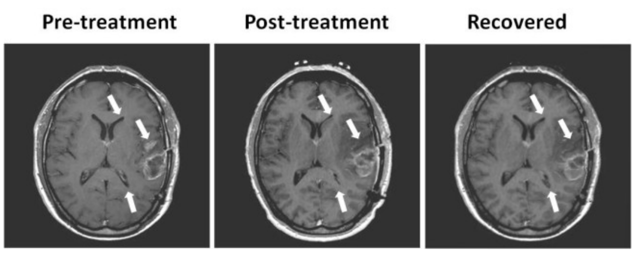

Fig. 2. Real MRI clinical case images elastic registration.

TABLE II
REGISTRATION ACCURACY IN CLINICAL DATA.

MRI Clinical Case

	ASD(mm)		Dmax(mm)		DICE	
	pre	post	pre	post	pre	post
Brain surface	2.01	0.64	5.73	5.73	0.97	0.99
Top left vent	0.66	0.33	2.59	0.82	0.86	0.93
Bottom left vent	2.06	0.43	4.63	1.16	0.37	0.91
Top right vent	1.88	0.63	4.10	2.46	0.72	0.91
Bottom right vent	1.43	0.98	4.10	4.10	0.72	0.83
mean	1.61	0.60	4.23	2.85	0.73	0.92
SD	0.59	0.25	1.13	2.06	0.23	0.06
median	1.88	0.63	4.10	2.46	0.72	0.91

IV. CONCLUSIONS

This work evaluated the accuracy of elastic registration guided by the particle filter (PF) with an optical flow process in 2D. In CT and MRI images of radiotherapy patients, in both simulated and real environment, registration showed good accuracy, both qualitatively and quantitatively. These results, in terms of accuracy, corroborate the advantages already mentioned on PF approach such as easy implementation, robustness to initial parameters and speed processing [7],[8], suggesting that extending it to a 3D registration process may be considered as a good new option for radiotherapy applications like patient's follow up treatment.

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