

Fast Non-Rigid Medical Image Registration using a Parameterized Surface and Anatomical Landmarks.

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Abstract

The paper presents a series of experiments which involve the use of the Fast Radial Basis Function algorithm for non-rigid medical image registration. The algorithm is a point-based registration technique which enables sub-second registration during the evaluation stage of standard-sized MR or X-ray CT datasets without loss of accuracy as compared to standard methods. In this paper we illustrate that the accuracy of the registration improves when using increasingly more salient feature points (i.e. landmarks and regular surfaces) without affecting the speed of the algorithm. Initially, a set of curves are extracted using a combined watershed and active contours algorithm, then tiled and converted to a regular surface using a global parametrization algorithm. Numerical results exhibit target registration errors less than 2mm on intra-subject registration of MR image datasets from the Alzheimer's Disease Neuroimaging Initiative (ADNI) Database whilst preserving sub-second performance for the Fast Radial Basis algorithm whereas competing algorithms exhibit slower performances.

1 Introduction

We aim to show that a previously introduced algorithm [9] for non-rigid medical image registration, called the fast RBF algorithm, is largely insensitive to the number of landmarks used in terms of its performance speed during the evaluation stage¹. Increasing the number of landmarks during registration should improve accuracy, provided the landmarks are accurately placed. Alternative algorithms will slow down the more landmarks are used. In previous research, we validated the fast RBF algorithm on single landmarks. To enable us to use many accurately placed landmarks - which is not practical by using single anatomical landmarks - we use corresponding² parameterized surfaces. The remainder of this paper describes the method we used to obtain parameterized corresponding surfaces, the fast RBF principle and an experiment comparing the fast RBF method to alternative non-rigid registration methods.

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¹The evaluation stage involves the application of a previously fitted model to the entire voxel dataset which is usually more time consuming than the 'calculation stage', i.e. when the model parameters are determined.

²The word 'corresponding' which is frequently used in this paper relates to the corresponding landmarks for each of the two volumes to be registered which - where this is not the case a '*' is used for clarity.

2 Methods and algorithms

2.1 Surface generation and parametrization

We first extract a set of curves along Z-slices from both images to be registered. For this purpose, two popular techniques, active contours and watersheds were used to create a sufficient number of curves (point sets). Both methods, when used individually, have certain limitations, i.e. the watershed segmentation method is sensitive to image noise, hence causing over-segmentation, whilst active contours suffer from initialization problems. Both techniques can overcome each other's limitations as the watershed algorithm provides initialization for the active contour whilst the latter smoothens the result hence avoiding over-segmented boundaries [2]. Once a boundary contour is obtained, we resample each curve with a fine set of points (at pixel level) into a coarser one (at edgel level) by continuously reducing a given set of points into a two point set based on the computation of a mid point value. This process terminates when the number of points in a given set is less than or equal to a user defined number. The final result is a set of corresponding boundary landmarks on each slice which are then triangulated to form a 3D surface by applying the advancing-front algorithm [6]. In order to remesh the 3D surface, we first need a suitable parametrization technique (conformal and equi-areal) to flatten the 3D surface and then need a resampling technique to convert it back to a parameterized 3D surface. We used the fast and robust algorithm of Yoshizawa et al. [11] to parameterize the original mesh and represent it on a unit square as a 2D mesh. Their technique is a global parametrization method based on a shape-preservation method originally proposed by Floater in [1]. After parametrization, we resample the 2D mesh using a regular 2D grid and find the corresponding* 3D spatial position in the original mesh for each vertex (point) of the 2D grid.

2.2 Fast Radial Basis Functions method

We assume a Radial Basis Function (RBF) formulation³ in 3D:

$$s(\mathbf{x}_i) = \sum_{j=0}^n \lambda(\mathbf{y}_j) \phi(\|\mathbf{x}_i - \mathbf{y}_j\|), i = 0, 1, \dots, m. \quad (1)$$

for $i = 1 \dots m$ evaluation points/voxels (targets) represented by the target vector \mathbf{x}_i , the spline parameters λ_j for $j = 1 \dots n$ landmarks represented by the source (landmark) vector \mathbf{y}_j .

Based on the work by Livne and Wright [5] and extended to 3D [8] the above equation can be simplified by representing the RBF on a regular coarse grid with fewer nodes than the full voxel set. The main principle of the fast RBF method is to encapsulate source and target points in separate grids of size H . It results in a two stage process conversion of the RBF in Equation 1. The first stage replaces the original **source** points with their corresponding grid points by using a centered p -th order tensor product interpolation:

$$\phi(\|\mathbf{x}_i - \mathbf{y}_j\|) = \sum_{j: J_k \in \sigma_j^{(k)}} \omega_{jJ_3} \omega_{jJ_2} \omega_{jJ_1} \phi(\|\mathbf{x}_i - \mathbf{Y}_{(J_1, J_2, J_3)}\|) \quad (2)$$

where $j = 0, 1, \dots, n$ and for dimension $k = 1, 2, 3$:

$\sigma_j^{(k)} := \left\{ J_k : |Y_{J_k}^{(k)} - y_j^{(k)}| < pH/2 \right\}$, where ω_{jJ_k} are the new centered p th-order interpola-

³The radial basis function ϕ can take several forms, but the biharmonic spline (BHS), $\phi(r) = r$, is optimal in minimizing the bending energy potential in 3D [7]

tion weights from the coarse centres $Y_{J_k}^{(k)}$ to the landmark positions $y_j^{(k)}$. The second stage replaces the original **target** points with their corresponding grid points using the same approach:

$$\phi(\|\mathbf{x}_i - \mathbf{Y}_{\mathbf{J}}\|) = \sum_{I_k \in \bar{\sigma}_i^{(k)}} \bar{\omega}_{iI_3} \bar{\omega}_{iI_2} \bar{\omega}_{iI_1} \phi(\|\mathbf{X}_{(I_1, I_2, I_3)} - \mathbf{Y}_{\mathbf{J}}\|) \quad (3)$$

where $i = 0, 1, \dots, m$, $\mathbf{J} = (J_1, J_2, J_3)$, and for dimension $k = 1, 2, 3$:

$\bar{\sigma}_i^{(k)} := \{I_k : |X_{I_k}^{(k)} - x_i^{(k)}| < pH/2\}$, where $\bar{\omega}_{iI_k}$ are the centered p th-order interpolation weights from the coarse evaluation point $X_{I_k}^{(k)}$ to the level h (original image grid size) evaluation point $x_i^{(k)}$. The procedure used to distribute the known RBF coefficients $\lambda(\mathbf{y}_j)$ at each landmark position to the surrounding nodes of grid \mathbf{Y} is called *anterpolation*.

3 Experiments

The aim of the experiments presented in this paper is to show the insensitivity in terms of speed of the fast RBF method to an increasing number of accurately placed landmarks, the latter aiming to improve the registration accuracy during evaluation. Five different methods are compared, which are: (1) Brute force (non-optimized) RBF; (2) Brute force (non-optimized) RBF with hardware acceleration; (3) Fast RBF; (4) Fast RBF with hardware acceleration; (5) Grid based approach by Levin et al. [4] with two different grid sizes⁴. The MR datasets of three subjects of the ADNI database (adni.loni.ucla.edu) were used and re-sampled to 256^3 with slice thicknesses of 1mm. These datasets were used to test intra-patient point-based non-linear registration from the original dataset to its natural deformed version (see Figure 1 columns 1 and 2 of second row).

To assess the accuracy of our technique, we use the *Target Registration Error* (TRE)⁵ and the *Normalized mutual Information* (NMI) (Studholme et al. [10]).

4 Results and Discussion

Table 1 shows that the NMI of the larger landmark set (475) is better than when using just 20 landmarks. The average TRE is slightly worse, however the standard deviation is substantially smaller despite being measured over a much larger set of validation points illustrating a statistically more significant result. The evaluation time of the fast RBF method (both software and hardware versions) is only marginally affected by increasing the number of landmarks with a factor of more than 20, unlike all other methods which are proportionally more affected. The %NMI metric shows the performance of the optimised techniques in comparison to the non-optimised ‘Brute force’ software based method (gold standard). The fast RBF method implemented in hardware exhibits the highest correspondence (99%+) implying minimal loss of accuracy due to fast RBF optimization and hardware acceleration.

5 Conclusion

We have evaluated the fast RBF non-rigid registration method for medical imaging data using parameterized surfaces to derive large numbers of anatomical landmarks. The algorithm

⁴Levin et al. [3, 4] proposed a method for accelerating point based non-rigid registration by using the fast tri-linear interpolation capability of modern graphics cards on a standard PC. Their implementation evaluates a thin-plate spline (TPS) warp at discrete points on a configurable sized grid that overlays each image data slice.

⁵The TRE is the RMS error between the homologous validation landmarks after registration.

20 landmarks	Eval. Time in sec.	NMI	%NMI	TRE in mm.
Brute force S/W	28.55(1.54)	1.202(0.043)	100.00	1.63(0.49)
Brute force H/W	0.51(0.05)	1.192(0.036)	99.1	1.63(0.49)
Fast RBF S/W 0.025	15.27(0.47)	1.202(0.043)	100.0	1.63(0.49)
Fast RBF H/W 0.025	0.53(0.04)	1.199(0.041)	99.6	1.63(0.49)
Grid 13	0.43(0.01)	1.144(0.066)	95.1	1.63(0.49)
Grid 138	16.31(1.08)	1.144(0.066)	95.1	1.63(0.49)
450+25 landmarks	Eval. Time in sec.	NMI	%NMI	TRE in mm.
Brute force S/W	486.48(4.02)	1.227(0.013)	100.00	1.81(0.20)
Brute force H/W	2.42(0.47)	1.214(0.027)	99.9	1.81(0.20)
Fast RBF S/W 0.025	31.15(1.04)	1.226(0.024)	100.0	1.81(0.20)
Fast RBF H/W 0.025	0.62(0.02)	1.221(0.021)	99.6	1.81(0.20)
Grid 13	2.69(0.06)	1.145(0.051)	93.4	1.81(0.20)
Grid 138	282.25(2.78)	1.142(0.052)	93.1	1.81(0.20)

Table 1: Results after applying a BHS basis function for non-rigid registration of the MR-T1 ADNI datasets of the same subject taken at different time points. 20 landmarks were used for training and 20 for validation in the upper half table. In the lower half table, 450 surface-based landmarks were used for training, while another 450 surface-based landmarks were used for validation, plus an additional 25 manually placed landmarks were used. All tests were run over 5 subjects. Values are averages with standard deviation in parentheses. The second column shows the evaluation time of the RBF in seconds. The third column shows the NMI. The next column shows the %NMI as compared to the Brute-Force Software used as the golden standard. The fifth and final column shows the TRE in mm. which is evaluated on the validation landmarks - note that the latter is the same for all methods as its calculation is based on the same BHS model.

when implemented in hardware yields sub-second evaluation times on a standard PC with high-end video adapter card. The evaluation (warp) time of the Fast RBF algorithm is significantly less susceptible to the number of landmarks used as compared to the tested competing methods. Considering that more accurately placed landmarks improve accuracy implies that this algorithm is favourable for applications where both speed and accuracy are of importance, such as in IGS (Image Guided Surgery). In the future we will use the parameterized surface and will do experiments on medical image data with a higher degree of non-rigid distortion.

References

- [1] M. S. Floater. Parametrization and smooth approximation of surface triangulations. *Computer Aided Geometric Design*, 14:231–250, 1997.
- [2] R. J. Lapeer, A. C. Tan, and R. V. Aldridge. Active watersheds: combining 3d watershed segmentation and active contours to extract abdominal organs from mr images. in: *T. Dohi, R. Kikinis (Eds.), Proceedings of the Medical Image Computing and Computer-Assisted Intervention-MICCAI 2002 Conference, Lecture Notes in Computer Science, Springer, Berlin, 2488:596–603, 2002.*
- [3] D. Levin, D. Dey, and P. J. Slomka. Acceleration of 3D, nonlinear warping using standard video graphics hardware: implementation and initial validation. *Comput Med Imaging Graph*, 28(8):471–483, Dec 2004.

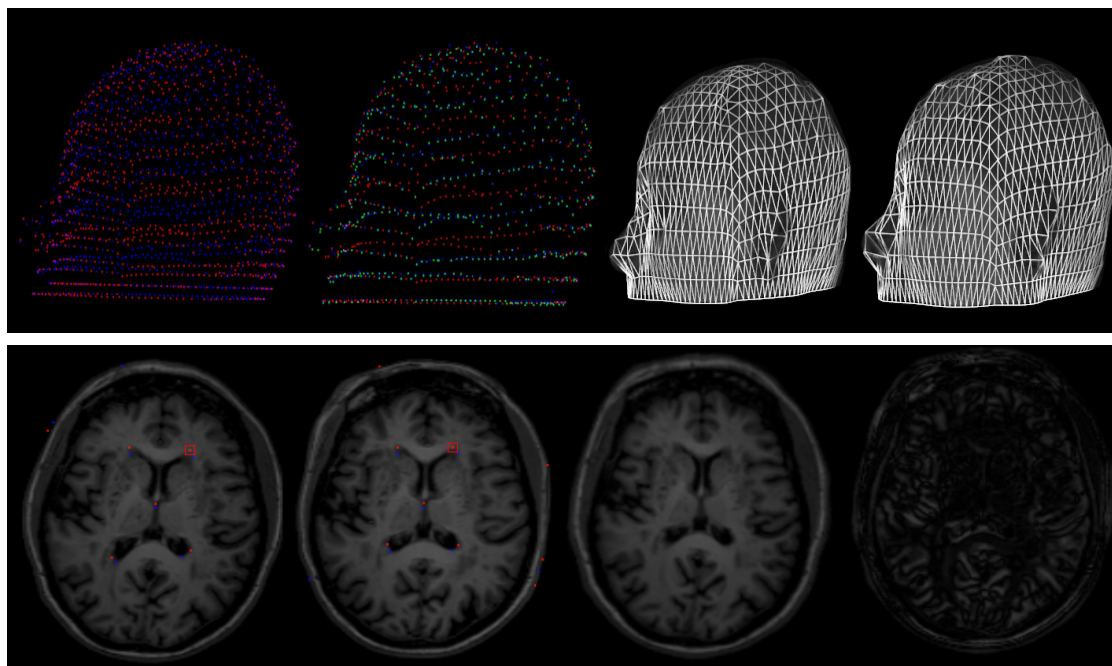


Figure 1: The first two images in first row shows the corresponding *training* and *validation* (red and blue) landmarks before registration, and after (red, blue and green respectively) registration, while the last two images show the corresponding parameterized surfaces. The second row from left to right show arbitrarily selected transverse slices from the full resolution MR datasets (ADNI database) of patient 002_S_0954. The first two images illustrate the original and deformed MR image before registration, while the last two images show corresponding registered and absolute difference images after the registration experiment, respectively.

- [4] D. Levin, D. Dey, and P. Slomka. Efficient 3D nonlinear warping of computed tomography: two high-performance implementations using OpenGL. In R.L. Galloway, Jr. and K.R. Cleary, editors, *Medical Imaging 2005: Visualization, Image-Guided Procedures, and Display. Proceedings of the SPIE*, volume 5744, pages 34–42, 2005.
- [5] O. E. Livne and G. B. Wright. Fast multilevel evaluation of smooth radial basis function expansions. *Electronic Transactions on Numerical Analysis*, 23:263–287, 2006.
- [6] S. H. Lo. A new mesh generation scheme for arbitrary planar domains. *International Journal for Numerical Methods in Engineering*, 21:1403–1426, June 1985.
- [7] K. Rohr. *Landmark-Based Image Analysis Using Geometric and Intensity Models*. Kluwer Academic Publishers, 2001.
- [8] R. Rowland. *Fast Registration of Medical Imaging Data using Optimised Radial Basis Functions*. PhD thesis, University of East Anglia, 2007.
- [9] R.S Rowland and R.J. Lapeer. Fast non-rigid registration of medical images: comparing the thin-plate and biharmonic splines. In *Medical Image Understanding and Analysis, MIUA 2008, Dundee*, pages 246–250, 2008.
- [10] C. Studholme, D. L. G. Hill, and D. J. Hawkes. An overlap invariant entropy measure of 3D medical image alignment. *Pattern Recognition*, 32:71–86, 1999.
- [11] S. Yoshizawa, A. Belyaev, and H. Seidel. A fast and simple stretch-minimizing mesh parameterization. In *In Proceedings of the Shape Modeling International*, pages 200–208, 2004.