Automated Multimodality Registration Using the Full Affine Transformation: Application to MR and CT Guided Skull Base Surgery

Colin Studholme, John A. Little,Graeme P. Penny,
Derek L.G. Hill, David J. Hawkes

Division of Radiological Sciences
United Medical and Dental Schools of Guy's and St. Thomas' Hospitals Guy's Hospital, London Bridge, London, SE1 9RT, UK

Abstract. We have used a twelve degrees of freedom global affine registration technique incorporating a multiresolution optimisation of mutual information to register MR and CT images with uncertain voxel dimensions and CT gantry tilt. Visual assessment indicates improved accuracy, without loss of robustness compared to rigid body registration.

1 Introduction

This papers presents an extension of voxel similarity based registration techniques to estimating global affine parameters between MR and CT images of the head. Current surgical planning and guidance work at our site has made use of accurate rigid registration of MR and CT images. Although estimates of machine scaling parameters are confirmed by phantom based image measurements, inspection of some clinically registered images has indicated visually detectable scaling differences in some cases.

Manufacturers typically claim a tolerance of around 3% in calibration accuracy when setting up medical imaging equipment. A discrepancy of $6mm$ may therefore be experienced over a $200mm$ field of view, which will be unacceptable in many applications. In addition we sometimes obtain patient images from other sites where such checks are not regularly applied and parameters such as CT gantry tilt are unknown. In order to reduce additional radiation dose to the patient, as well as costs, it is important that the need to re-scan locally is kept to a minimum.

Image distortion in MR cannot be corrected by using scaling and skew factors alone. In our experience, however, scaling and skew errors are often larger than errors arising from other components of MR distortion for many clinical datasets. The ability to automatically detect and estimate discrepancies in scaling and skew parameters between images would therefore be a useful check to ensure spatial integrity of the data as part of normal clinical registration protocols.

Voxel similarity based approaches [3, 5], particularly those making use of mutual information measures between images [6, 2, 7, 4] have been shown to provide a robust and fully automatic method of estimating rigid registration

Published in: Proceedings of Visualisation in Biomedical Computing, Hamburg, Germany, Sept. 1996, Eds. Karl Heinz Hohne and Ron Kikinis, pp. 601-606, Springer, Lecture Notes in Computer Science, ISBN 3-540-61649-7.

parameters. We demonstrate that the estimate of an affine rather than rigid transformation can improve accuracy, without compromising robustness, and without a prohibitive increase in computation time.

2 Method

2.1 Mutual Information and Image Registration

In this work we have used the measure of mutual information $I(M;C)$ as proposed by Viola and Wells [6, 7] and Collignon [2]. This was evaluated from a discrete estimate of the joint, $p\{m,c\}$, and separate, $p\{m\}$ and $p\{c\}$ probability distributions, of the MR and CT intensities M and C occurring in the volume of overlap of the two images:

$$I(M;C) = \sum_{m \in M} \sum_{n \in C} p\{m,c\} \log \frac{p\{m,c\}}{p\{m\}p\{c\}} \tag{1}$$

2.2 Registration Parameters and Optimisation

In order to efficiently optimise affine parameters we need to be able to equate changes in translations, rotations, scalings and angles of skew. Global voxel similarity measures provide a bulk measure of voxel displacement. A reasonable choice of relationship between equivalent small changes in the parameters is one which results in the same mean displacement of voxels in the overlap of the images. For simplicity we assume a cuboidal volume of overlap $\mathcal{F}_x \times \mathcal{F}_y \times \mathcal{F}_z$ between MR volume V_m and CT volume V_c. For translations take the step sizes in each direction $\{\delta t_x, \delta t_y, \delta t_z\}$ to be equal to δt. For changes in rotation, scale and skew, we can integrate the displacements of points within the volume of overlap to find the mean displacement which we equate to δt. This gives us,

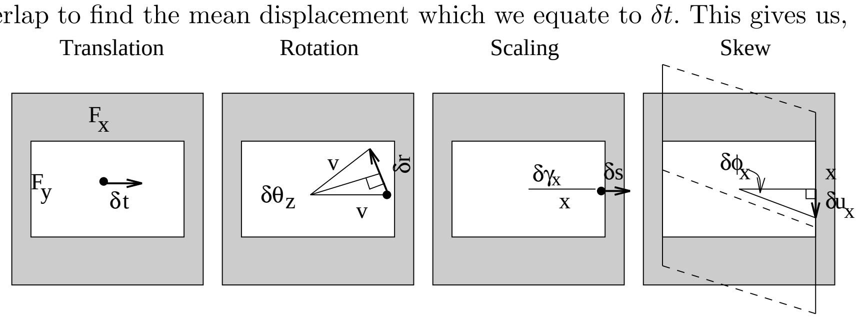

Fig. 1. Equivalent displacements for small changes in different affine parameters

$$\delta\theta_z = 2\sin^{-1}\frac{6\delta t \mathcal{F}_x \mathcal{F}_y}{\mathcal{K}},\ \delta\gamma_x = 4\delta t/\mathcal{F}_x,\ \delta\phi_x = \tan^{-1}(4\delta t/\mathcal{F}_x). \tag{2}$$

and equivalent formula for parameters in the other planes and where,

$$\mathcal{K} = \mathcal{F}_x^3 \left\{ \frac{\sin\alpha_{xy}}{\cos^2\alpha_{xy}} + \ln|\tan(\frac{\pi}{4} + \frac{\alpha_{xy}}{2})| \right\} + \mathcal{F}_y^3 \left\{ \frac{\sin\beta_{xy}}{\cos^2\beta_{xy}} + \ln|\tan(\frac{\pi}{2} - \frac{\alpha_{xy}}{2})| \right\}$$

Published in: Proceedings of Visualisation in Biomedical Computing, Hamburg, Germany, Sept. 1996, Eds. Karl Heinz Hohne and Ron Kikinis, pp. 601-606, Springer, Lecture Notes in Computer Science, ISBN 3-540-61649-7.

and $\alpha_{xy} = \tan^{-1}(\mathcal{F}_y/\mathcal{F}_x)$ and $\beta_{xy} = \pi/2 - \alpha_{xy}$.

To optimise the parameters we evaluate $I(M;C)$ over the the set of 13 (for rigid) or 25 (for affine) transformations $\mathcal{T}(T_0)$. These are the current starting estimate and the starting estimate with increments and decrements of each of the 3 translations $\{\delta t_x, \delta t_y, \delta t_z\}$, 3 rotations $\{\delta\theta_x, \delta\theta_y, \delta\theta_z\}$, 3 scaling factors $\{\delta\gamma_x, \delta\gamma_y, \delta\gamma_z\}$ and 3 skew angles $\{\delta\phi_x, \delta\phi_y, \delta\phi_z\}$. We choose the best estimate of the registration transformation T_1 for the value of I such that:

$$T_1 = \min_{T \in \mathcal{T}(T_0)} \{I(M(V_m \cap TV_c), C(V_m \cap TV_c))\} \tag{3}$$

If $T_{n+1} \neq T_n$ then we can repeat the search with $\mathcal{T}(T_{n+1})$ until $T_{n+1} = T_n$. The step sizes can then be reduced and the search continued, the minimum values of step size determining how close we get to the optimum transformation. Starting with low resolution versions of the images and large step sizes, we apply this optimisation, reducing the step size and increasing the image resolution. Experimentally we have found this provides both computational efficiency and robustness to starting estimate.

2.3 Test Data

Three clinically acquired image pairs were used for the tests. Firstly an MR and CT volume covering a significant portion of the skull with slice thicknesses of 1.2mm and 2.0mm respectively. Secondly a more typical truncated CT volume limited to an axial extent of 31mm in the skull base with corresponding full brain volume MR. Both these images originated from scanners at another site and contained errors in slice thickness and skew angle estimates. Thirdly a locally acquired pair of images including a relatively large volume CT for which scanner quality control had been performed.

Following optimisation of mutual information the results were visually inspected, and for patient A compared to phantom measurements. In order to assess the precision of the estimate for patient A, randomised rigid starting estimates were created by adding random translations (of magnitude 10 mm) and random rotations (of magnitude of 10 degrees) to the six rigid estimates. Optimisation was then initiated from 50 of these orientations and the results recorded.

3 Results

Table 1 shows transformation estimates following optimisation of rigid and affine parameters. The right of figure 2 shows example slices through the MR volume for patient A illustrating the improvement provided by registration including scale estimates. It is interesting to note that when scaling is not included the rigid registration is biased toward better alignment around the skull base. This is presumably because of the larger amount of registration information available in this region. The left of figure 2 shows (a) the poor rigid estimate for patient B

Published in: Proceedings of Visualisation in Biomedical Computing, Hamburg, Germany, Sept. 1996, Eds. Karl Heinz Hohne and Ron Kikinis, pp. 601-606, Springer, Lecture Notes in Computer Science, ISBN 3-540-61649-7.

Registration Parameter Estimates

Parameter	Patient A Rigid	Patient A Affine	Patient B Rigid	Patient B Affine	Patient C Rigid	Patient C Affine
$t_x$mm	-2.83 (0.13)	-2.83 (0.26)	-1.70	-1.32	8.71	8.53
$t_y$mm	-2.50 (0.59)	-2.71 (0.09)	9.30	9.82	32.83	32.65
$t_z$mm	-26.34 (0.20)	-26.34(0.10)	-45.8	-45.0	-0.24	0.08
θ_x°	1.09 (0.32)	2.09 (0.31)	38.6	38.24	24.41	24.08
θ_y°	-2.38 (0.33)	-1.59 (0.31)	-0.88	-1.0	-6.29	-6.15
θ_z°	0.00 (0.18)	0.00 (0.24)	5.05	5.17	-0.65	-1.23
γ_x	1.00	1.00 (0.0014)	1.00	1.00	1.00	0.99
γ_y	1.00	0.98 (0.0026)	1.00	0.99	1.00	1.00
γ_z	1.00	1.06 (0.0069)	1.00	1.65	1.00	0.96
ϕ_x°	0.00	0.00 (0.11)	0.00	0.23	0.00	0.51
ϕ_y°	0.00	0.71 (0.43)	0.00	-0.04	0.00	-0.11
ϕ_z°	0.00	1.71 (0.27)	0.00	-8.0	0.00	-0.74

Table 1. Comparison of registration estimates for Patient A, B and C following optimisation of rigid parameters, and all affine parameters.

using the supplied scaling and gantry tilt angles, and (b) the significant improvement provided by a full affine parameter optimisation. In order to investigate the origin of the scaling error for patient A, an MR and CT visible point landmark phantom was imaged in the scanners using the same protocols. Distances between points in the images could then be measured by interactive location of the centres of markers. Equivalent distances on the phantom were measured and indicated a seven percent reduction between the phantom and its CT image in the axial direction. This figure was later confirmed as a calibration error in the bed speed for spiral acquisitions.

The figures in brackets in table 1 show the standard deviations of final parameter estimates from 50 randomised starts around the first estimate. The standard deviation of the registration parameters is small for both the rigid and affine solutions and no significant increase is noted when the number of parameters is increased, with in one case (t_y) an appreciable decrease.

4 Discussion

We have shown experimentally that when extending the transformation estimate to 12 parameters, the robustness to starting estimate, robustness to limited field of view, and the precision of the final results are maintained. Typical execution times are increased from 10 to 24 minutes on a Sparc Station 20/61 for dataset C covering a large volume of the head. Where computing time needs to be minimised and some parameters are known accurately, the dimensionality of the search space can be reduced appropriately.

Given two images we can only estimate the discrepancy in scaling and skew estimates between the images, we do not know which has the correct dimensions, so we cannot rely on this approach to replace routine quality assurance procedures. This is particularly important when the images are to be registered to the

Published in: Proceedings of Visualisation in Biomedical Computing, Hamburg, Germany, Sept. 1996, Eds. Karl Heinz Hohne and Ron Kikinis, pp. 601-606, Springer, Lecture Notes in Computer Science, ISBN 3-540-61649-7.

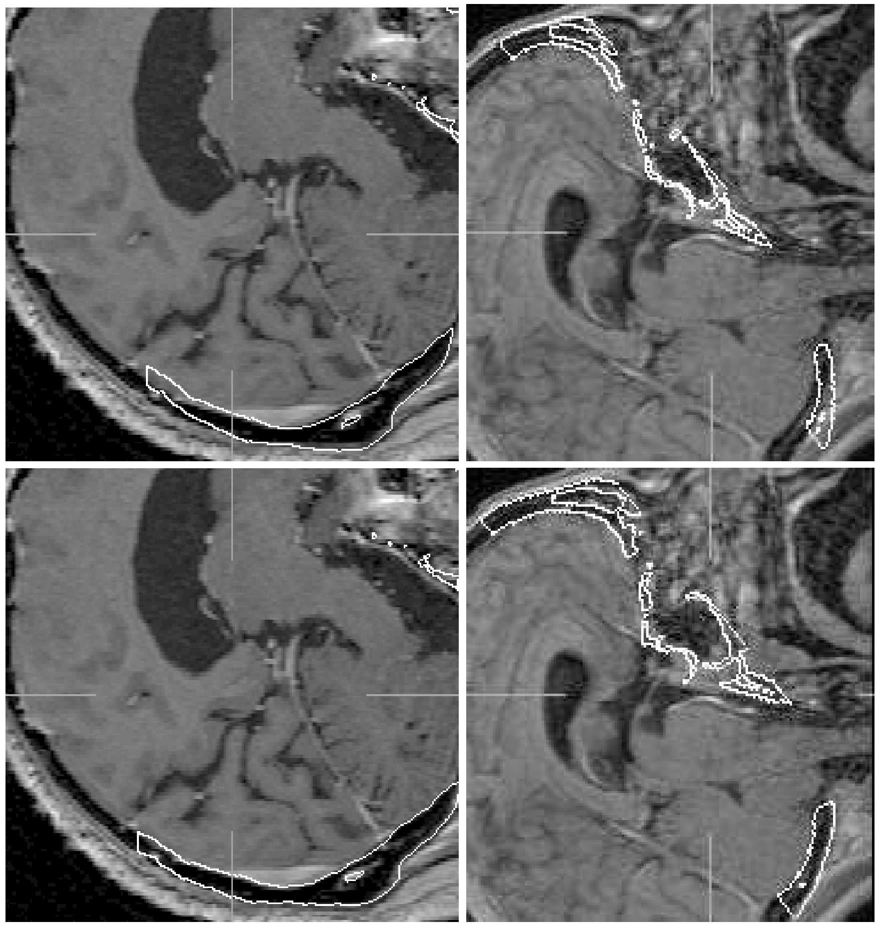

Fig. 2. Sagittal slices through the MR volumes for patient A (left) and patient B (right) with the CT bone boundary, obtained by intensity threshold, overlaid in white showing (top) rigid transformation estimate, and (bottom) affine estimate

patient in surgery. However we have found that this approach is very useful in highlighting discrepancies in clinical data that merit further investigation. This is particularly true when combining MR with CT acquired in the skull base, where limited axial extent leads to difficulties in visually distinguishing small errors in skew or scale factors from rigid alignment errors.

Most concern has been expressed about MR image integrity, because of the process by which scaling is determined in MR and because patient induced distortion can affect image quality [1]. In two of the three examples given in this paper subsequent investigation demonstrated that the major source of the error was in the CT acquisition. In one case a hardware maladjustment in bed movement led to a 7 percent error in axial scaling during a helical scan sequence, while in the other an incorrect slice interval was provided in the image header information. We have not found any significant errors in transaxial scaling in

Published in: Proceedings of Visualisation in Biomedical Computing, Hamburg, Germany, Sept. 1996, Eds. Karl Heinz Hohne and Ron Kikinis, pp. 601-606, Springer, Lecture Notes in Computer Science, ISBN 3-540-61649-7.

CT data.

One of the risks of using fully automated image registration techniques, is that the operator will fail to spot deficiencies in the data, and that the resulting incorrectly registered images will be used inappropriately for diagnosis, treatment planning or image guided surgery. MR distortion, and artifacts caused by patient motion may still lead to significant errors in some cases. Further work is underway using phantoms to provide a better assessment of the accuracy of skew and scaling estimates provided by the approach. Additional degrees of freedom could be added to the registration algorithm to make it possible to automatically detect, and perhaps even correct, significant MR distortion, or the slice alignment errors that arise when a patient moves between slices in a CT, or 2D multi-slice MR acquisition.

Acknowledgements

We are grateful to EPSRC, Guy's and St Thomas's Hospital NHS Trust and Philips Medical Systems (ICS/AD) for their financial support of this work. We are grateful for the support and encouragement of Prof. Michael Maisey, Dr. Tim Cox, Dr. Alan Colchester, Prof. Mike Gleeson, Mr Tony Strong and Mr Charles Polkey in this work. We thank Dr Jason Zhao for assisting in making the data for patient B available to us and the radiological staff at Guy's, St Thomas's and the Maudsley Hospitals for their assistance in acquiring the data for patient A and the phantom.

References

1. H. Chang and J.M. Fitzpatrick. A technique for accurate MR imaging in the presence of field inhomogeneities. *IEEE Trans. Med. Imaging*, 11:319–329, 1992.
2. A. Collignon, F. Maes, D. Delaere, D. Vandermeulen, P. Suetens, and G. Marchal. Automated multimodality image registration using information theory. In Bizais Y., Barillot C, and Di Paola R., editors, *Proceedings of Information Processing in Medical Imaging*, pages 263–274, 1995. Brest, France.
3. D.L.G. Hill, C. Studholme, and D.J. Hawkes. Voxel similarity measures for automated image registration. In *Proceedings of Visualisation in Biomedical Computing*, pages 205–216, 1994. Rochester Mn.,U.S.A.
4. C. Studholme, D.L.G. Hill, and D.J. Hawkes. Automated 3D registration of truncated MR and CT images of the head. In D. Pycock, editor, *Proceedings of the British Machine Vision Conference*, pages 27–36. BMVA, 1995. Birmingham.
5. P.A. Van den Elsen, E.J.D. Pol, T.S. Sumanawaeera, P.F. Hemler, S. Napel, and J.R. Adler. Grey value correlation techniques used for automatic matching of CT and MR brain and spine images. In *Proceedings of Visualisation in Biomedical Computing*, pages 227–237, 1994. Rochester Mn.,U.S.A.
6. P.A. Viola and W.M. Wells. Alignment by maximisation of mutual information. In *Proceedings of the 5th International Conference on Computer Vision*, pages 15–23, 1995.
7. W.M. Wells, P. Viola, and R. Kikinis. Multimodal volume registration by maximization of mutual information. In *Proceedings of the 2nd annual international symposium on Medical Robotics and Computer Assisted Surgery*, pages 55–62, 1995. Baltimore, U.S.A.

Published in: Proceedings of Visualisation in Biomedical Computing, Hamburg, Germany, Sept. 1996, Eds. Karl Heinz Hohne and Ron Kikinis, pp. 601-606, Springer, Lecture Notes in Computer Science, ISBN 3-540-61649-7.