International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:1, No:7, 2007

Non-Rigid Registration of Medical Images using an Automated Method

Panos Kotsas

***Abstract*—**This paper presents the application of a signal intensity independent registration criterion for non-rigid body registration of medical images. The criterion is defined as the weighted ratio image of two images. The ratio is computed on a voxel per voxel basis and weighting is performed by setting the ratios between signal and background voxels to a standard high value. The mean squared value of the weighted ratio is computed over the union of the signal areas of the two images and it is minimized using the Chebyshev polynomial approximation. The geometric transformation model adopted is a local cubic B-splines based model.

***Keywords*—** Medical image, non-rigid, registration.

I. Introduction

IMAGE registration is the process of geometrically aligning two images so that corresponding voxels/pixelscan be superimposed on each other. There are several applications of image registration [1]. Examples are remote sensing, medicine, cartography, and computer vision.

In the medical field image registration is used for diagnostic purposes when images of the same anatomical structure must be superimposed on each-other. Registration methods are used [1] for combining computer tomography (CT) and NMR data to obtain more complete information about the patient, for monitoring tumor growth, for treatment verification, for comparison of the patient's data with anatomical atlases. The image registration methods can be divided into rigid and non-rigid. Rigid registration techniques adjust for rotations and translations only whereas non-rigid techniques assume a non-linear transformation model and can adjust for image warping.

This paper presents the application of a signal-intensity independent registration criterion for registration of medical images. The criterion is the mean squared value of the weighted ratio image. The criterion is computed explicitly for n Chebyshev points in a [-A,+A] interval and it is approximated using the Chebyshev polynomials for all other points in the interval. For rigid body registration rotations and translations are adjusted. For non-rigid body registration the local geometric transformation model presented in [2] based on cubic B-splines is used and the parameters of the transformation are adjusted in the same way with the rigid case.

Manuscript received July 7, 2005.

P. Kotsas is with the Greek Ministry for the Environment (Organization of Thessaloniki) as a special scientist in signal processing; (phone: +32-310-886048; fax: +32-310-825151; e-mail: pkotsas@orth.gr).

II. Methods

Given two superimposed non-registered images two types of areas can be identified. The areas where signal voxels/pixels superimpose with signal voxels/pixels and the areas where signal voxels/pixels superimpose with background voxels/pixels. In this paper the registration function is defined as the mean squared value of the weighted ratio image. The ratio is computed on a voxel per voxel basis and weighting is performed by setting the ratios between signal and background voxels to a standard high value. The mean value is computed over the union of the signal areas of the two images.

The rigid body registration algorithm [6,7] works with this function as following:

- The signal areas are segmented from the background areas. This is done with the fuzzy k-means [3] with k=3 clusters. The threshold is defined as the mean value of the centers of the two lower clusters.
- One of the two images is defined as the reference image. The other image is aligned to the reference and is referred to as the reslice image because in the 3D registration case it has to be resliced after alignment
- When the images have non-cubic voxel structures, they are interpolated using a trilinear interpolation routine.
- The main iteration loop is entered and one of the N geometric transformation parameters is adjusted with each iteration.
- For this parameter the reslice image is transformed at n=4 Chebyshev points [4] in the [-18, +18] transformation units interval and for these points the registration function is computed explicitly. As reported in [4] Chebyshev approximation may be enough when the function is analytic. The transformation units are degrees for rotations and voxels for translations. The approximated function has a point of minimum which is considered as the adjustment value of the geometric transformation parameter. Using this value, the reslice image is transformed.

- The adjustment values computed for each transformation parameter in different iterations are summated to give the final adjustment value. Convergence for a transformation parameter is achieved when two iterations that adjust this transformation parameter give adjustment values less than one transformation unit.

The non-rigid body registration algorithm works as following:

- The signal areas are segmented from the background areas with a user defined threshold.
- A local elastic geometric transformation model presented in [2,5] that uses cubic B-splines is used. The local B-spline deformation model is obtained by using a scaled version of the B-splines : $g(x)=x+\sum_{j\varepsilon Ic\subset Z^N} c_j \beta_{nm}(x/h-j)$ where n_m is the degree of splines used, and h is the knot spacing.
- The h parameter of the model is defined as h=32 for image dimensions 256x256 and the splines are cubic B-splines .
- The registration function is minimized iteratively with n=4 Chebyshev points for A=18 in the range of values of the geometric transformation parameters.
- One parameter is adjusted with each iteration.

III. Results

The rigid body form of the method was presented in [6,7]. 3D MR images from ten patients from the database of the Cleveland Clinic Foundation were used. The images were interleaved T1-weighted and T2-weighted studies. The T2 study was transformed using ten arbitrary rigid 3D transformations and then registered back to the T1 study. The experiments were performed at half resolution of 1.8mm. 3-5 iterations per geometric transformation parameter are needed. The nature of the similarity criterion is multiresolutional. When the resolution is halved both the high value areas and the area over which they are averaged are equally divided. The average rotational error was found to be 0.36degrees and the average translational error 0.36mm giving sub-voxel accuracy. In no experiment convergence to a local minimum occurred. The method performed well in the presence of high noise areas.

For non-rigid registration the 2D form of the method has been implemented. The MR scan was transformed using the local geometric transformation model and then registered using the method.

Figure 1 shows an example of the non-rigid registration experiment. The result is after 9 iterations per parameter of the registration algorithm but close results have been obtained after the 6th iteration. Figure 2 shows the areas of misregistration after iterations 0,1,2,3,4,5,6,9.

No convergence criterion has been yet defined for the non-rigid case. The value of the registration function starts from a high value, it reduces significantly initially but after some iterations it shows no further significant reduction. Therefore a convergence criterion could be the percentage of the reduction of the registration function but this has not been tested.

Some of the parameters due to their local effect do not affect the value of the registration function and the iteration adjustment value for these is set to zero. This is identified by detecting whether the values of the registration function (as it is extrapolated) are equal for -18 , +18 and 0.

In the result shown in figures 2,3 the registration error for the internal areas of the image is due to the fact that the thresholding method used sets to zero some internal image areas in the reference image.

When the signal intensities are viewed the internal areas of the images are misregistered due to the binary form of the method but the shape of these areas tends to improve. Figures 3,4 show the signal areas of the reslice image after iterations 9 and 15. It would be interesting to see how this effect is reduced if a segmentation routine is used for the internal structures and the signal over background criterion becomes signal over signal that belong to different clusters.

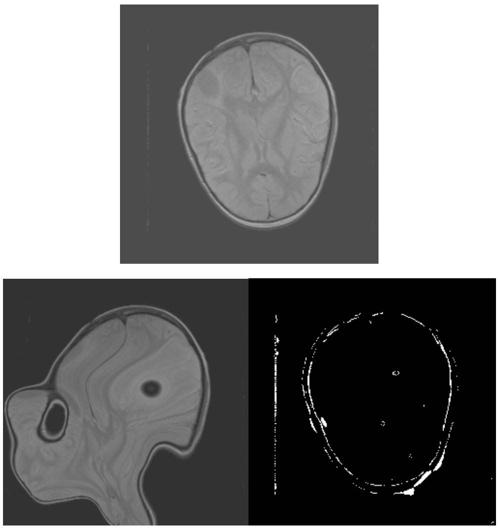
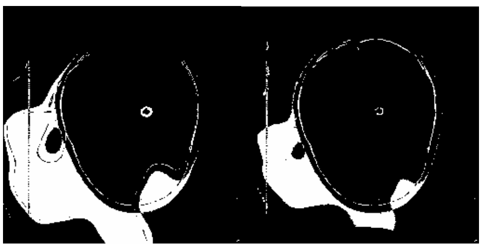
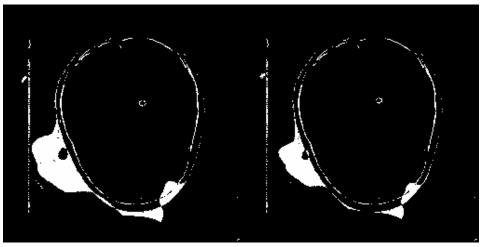


Fig. 1 Top row: Reference image, Second row left: Reslice image before registration, Second row right: areas of non-overlap after iteration 9



Initial misregistration Iteration 1



Iteration 2 Iteration 3

Iteration 4 Iteration 5

Iteration 6 Iteration 9

Fig. 2 Dynamic behavior of the algorithm for 2D non-rigid registration. Areas of non-overlap after iterations 0,1,2,3,4,5,6,9

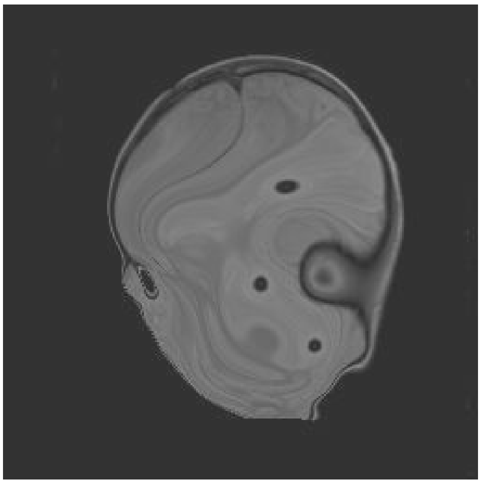


Fig. 3 Signal intensities after iteration 9

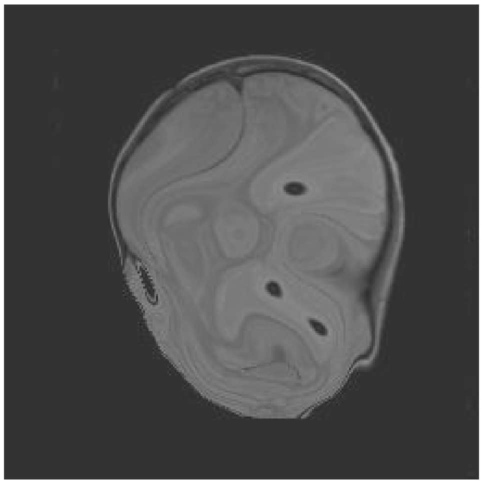


Fig.4 Signal intensities after iteration 15

IV. Conclusion

A method for image registration was presented and was applied to medical images that were treated as binary objects. The method minimizes a registration criterion which is defined as the mean squared value of the weighted ratio of two images. The method minimizes this criterion iteratively using the Chebyshev polynomial approximation functions. A few number of Chebyshev points (n=4) are needed for 3D rigid and 2D non-rigid registration. The method gives sub-voxel accuracy for rigid body registration and good results for non-rigid body registration. In no experiment convergence to a local minimum occurred even in the presence of high initial misregistration. The method performed well for 3D rigid registration at half resolution. The nature of the similarity criterion is multiresolutional. High noise areas did not affect the accuracy of the method.

Future research may address the application of the non-rigid method using the internal structures as segmented by an image segmentation routine.

References

[1] B.Zitova, J. Flusser, “Image registration methods: A survey”, Image and Vision Computing 21 (2003) pp977-1000

[2] J. Kybic and M. Unser, “Fast parametric elastic image registration”, IEEE Transactions on Image Processing Vol 12, No 11, Nov 2003, pp 1427-1442

[3] L.O.Hall, A.M.Bensaid, L.P.Clarke, R.P.Velthuizen, M.L. Silbiger et. Al. “ A comparison of neural networks and fuzzy clustering techniques in segmenting magnetic resonance images of the brain”, IEEE Trans. Neural Netw. 2 (1992), pp672-683.

[4] W.H.Press, S.A.Teukolsky, W.T.Vetterling, B.P.Flannery, Numerical recipes in C, The art of scientific computing, 2nd edition, Cambridge University Press, Cambridge 1992.

[5] J.Kybic, P. Thevenaz, A. Nirkko, M.Unser, “Unwarping of unidirectionally distorted EPI images”, IEEE Transactions on Medical Imaging, vol.19, no.2, pp80-93, Feb. 2000.

[6] P.Kotsas, S. Malasiotis, M. Strintzis,D.W.Piraino and J.F.Cornhill, “A fast and accurate method for registration of MR images of the head”, International Journal of Medical Informatics 52(1998) pp167-182.

[7] P.Kotsas, “A new automated method for three dimensional registration of MR images of the head”, Master’s Thesis, Dept. of Biomedical Engineering, The Ohio-State University.