Rigid and Non-rigid Registration of Binary Objects using the Weighted Ratio Image

Panos Kotsas, Tony Dodd

***Abstract*—**This paper presents the application of a signal intensity independent similarity criterion for rigid and non-rigid body registration of binary objects. 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 raios 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.

***Keywords*—**rigid and non-rigid body registration, binary objects

I. Introduction

IMAGE registration is the process of geometrically aligning two images so that corresponding voxels/pixels can be superimposed on each other. There are several applications of image registration [4]. 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 [4] 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 binary objects. 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.

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. Fig. 1 illustrates the registration function.

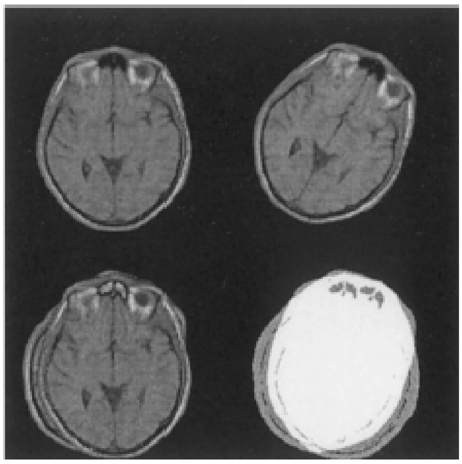

Fig. 1 First row, one scan and its rotation by 30°; Second row, two scans when superimposed give two different types of data. In the white area, the registration function is computed with the use of signal voxels only, whereas in the gray area, both signal and background voxels are used. The ratio of the two images is weighted by setting the ratio values in the gray area to a standard high value.

The rigid body registration algorithm 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.

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- 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 Chebyshev points [5] in the [-18, +18] transformation units interval and for these points the registration function is computed explicitly. 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 in the same way as the rigid case. It must be noted here that the threshold can be user defined and not necessarily automatically computed.
- A local elastic geometric transformation model presented in [2,9] 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 in the same way as in the rigid body case with n=4 for A=18 in the range of values of the geometric transformation parameters.
- One parameter is adjusted with each iteration.

III. Results

For rigid body registration 3D MR images from ten patients from the database of the Cleveland Clinic Foundation were used [1]. 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 limits used were -30 to +30° for xy rotation, -10 to +10° for yz and zx rotations, -10 to +10 mm for x and y translations and -5 to +5 mm for z translation. The experiments were performed at half resolution of 1.8mm. 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. It must be noted here that in no experiment convergence to a local minimum occurred. The method performed well in the presence of high noise areas.

In a different type of rigid body experiments the data of a second examination date were registered to the data of the first examination date. Figure 2 illustrates one such experiment with the use of surface renderings.

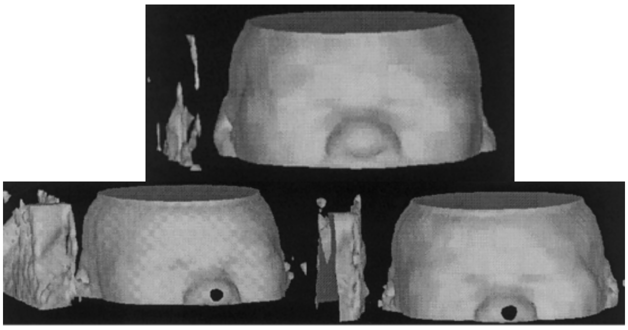

Fig. 2. T1–T2 registration experiments example: Top, Reference T1 volume; Bottom left, Reslice T2 volume before registration; Bottom right, Reslice T2 volume after registration.

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 3 shows an example of the non-rigid registration experiment. The result is after 25 iterations per parameter of the registration algorithm but close results have been obtained after the 9th iteration.

IV. Discussion

A method for rigid and non-rigid body registration was presented and was applied to medical images that were treated as binary objects. The method minimizes a similarity criterion that is defined as the mean squared value of 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 initial 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 rigid body method using the projections and the outer surfaces and the non-rigid method using the internal structures as segmented by a medical image segmentation routine.

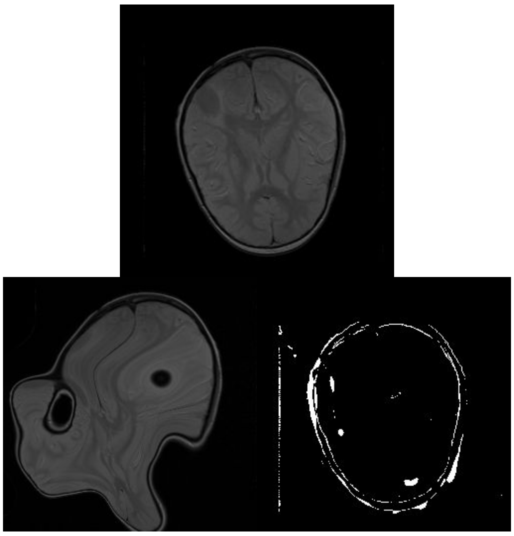

Fig. 3 Top row: Reference image, Second row left: Reslice image before registration, Second row right: zero-areas of non-overlap after registration.

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