# Piecewise-Quadrilateral Registration with Application to Contrast-Enhanced Breast MR Images

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## Introduction

Accurate registration of dynamic contrast-enhanced breast MR images is valuable for proper identification of lesions. Unfortunately many currently available registration algorithms require several hours of time to register a pair of 3D volumes, or require user intervention (e.g. to identify landmarks). This makes it difficult to add registration to an existing clinical workflow, and ensure that the radiologist is able to examine the registered images while the patient is still present. Herein, we present a registration technique which is currently in regular use in a research MRI environment, providing automatic registration of 8 sets of contrast-enhanced 3D volumes and requires only 3 minutes of post-processing. This speed ensures that, in future, should the need arise to scan more images than the current 5 per breast we perform at present (e.g. for compartmental analysis), we would still be able to register the post-contrast images in a reasonable time. Furthermore, the algorithm has shown to scale very well to multiple processors, and hence can be accelerated simply by adding more machines to our cluster.

## Method

All data sets used in our research were acquired on a 1.5T GE Signa scanner following informed consent from participants. Bilateral volume acquisitions (SPGR) of sagittal T1-weighted images [1] were acquired, without fat saturation. A single pre-contrast volume was scanned, followed by an injection of Gd-DTPA (0.1 mmole/kg) contrast agent, and the acquisition of four post-contrast image data sets. Each bilateral volume was acquired with 28 slices of 256x256 pixels resulting in an in-plane resolution of approximately 0.7mm and slice separation of 2-3mm. Each time point of the post-contrast data was then registered to the pre-contrast data.

The registration algorithm we present produces a piecewise quadrilateral transform over a fixed grid, driven by optical flow. At each stage of the algorithm, a regularized optical flow problem is solved to find new grid points. Using trilinear interpolation between the grid points, a new output estimate is produced. At the end of each iteration, the mutual information between the current output estimate and the target image is computed. If the mutual information has decreased, the iteration is abandoned and restarted with the regularization constraint relaxed. Once the regularization constraint has been relaxed beyond a given threshold (and mutual information still does not increase), the algorithm terminates.

The algorithm benefits significantly from a sparse structure (as grid points only interact with neighbouring grid points). This sparsity is exploited during the computational phase of each iteration, reducing the time required. Furthermore, the bottleneck step of the algorithm may be broken down into smaller pieces, which may safely execute in parallel. Our current implementation executes on a cluster of eight 1 Ghz Pentium III processors.

To validate the algorithm, we simulated a non-rigid deformation with radial basis functions. Control points were placed along the surface contour of the breast, and displaced. The exact displacement of individual voxels was recorded. The non-deformed image was registered to the deformed image, and the output voxel

displacements were recorded and compared to the known correct values. These tests were also performed by mapping the non-deformed baseline image to a deformed image with simulated contrast uptake, to verify that the algorithm performs adequately despite the contrast change. Three different test images were used, with three time points for each (one baseline, and two post-contrast). The first test image had simulated contrast uptake over a medium volume (approx. 20 cm<sup>3</sup>). The second image had contrast uptake over a small volume (approx. 1 cm<sup>3</sup>). The final image had a very bright contrast uptake over most of the breast (approx. 280 cm<sup>3</sup>).

## **Results and Discussion**

Our validation results (see Table 1) show that the algorithm significantly reduced misregistration in every case. In our second test, fewer than 5% of voxels were misregistered by more than one voxel (approximately 0.7mm), while in our first test, fewer than 0.5% of voxels had this property. Unfortunately, in our third case, the simulated region of contrast was large and sharp, which interfered with the optical flow calculations. This suggests that these particular cases are not well-suited to optical flow methods. As this was selected to be a particularly challenging case, this result was to be expected.

Taking a sample of 57 consecutive screening exams, each with 8 post-contrast volumes registered to their respective pre-contrast volumes, we found that mutual information was improved by an average of 7.65% by registration. In particular, in 11 exams, the average improvement was over 10%, yielding a significant reduction in motion artifacts.

### Conclusions

This algorithm has shown itself to be effective in regular use for screening exams. Our validation studies show that the algorithm is able to accurately identify and compensate for breast motion. The algorithm's speed and ability to work without user intervention makes registration clinically feasible as part of the regular scanning workflow.

### References

- [1] Warner E, Plewes DB, Hill K, et al, Surveillance of BRCA1 and BRCA2 Mutation Carriers with Magnetic Resonance Imaging, Ultrasound, Mammography, and Clinical Breast Examination. Journal of the American Medical Association, 2004. 292(11): p. 1317-1325.
- [2] Barber DC and Hose DR, Automatic segmentation of medical images using image registration: diagnostic and simulation applications, J. of Medical Engineering and Technology, accepted July 2004.

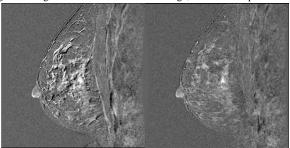


Figure 1:	Subtracted slice from breast MR image before	
registration	(left) and after registration (right).	

Test		max	mean	$\operatorname{std}$	prop
$\mathbf{S1}$	unreg	12.3914	4.2299	2.9593	0.8291
	pre	1.8789	0.2086	0.2064	0.0029
	post $1$	1.8761	0.2184	0.2063	0.0029
	post $2$	1.8628	0.2357	0.2136	0.0034
$\mathbf{S2}$	unreg	9.5608	3.2123	2.0493	0.8130
	pre	3.1740	0.2180	0.3748	0.0467
	post $1$	3.1740	0.2267	0.3755	0.0469
	post $2$	3.1740	0.2267	0.3754	0.0468
<b>S</b> 3	unreg	12.9907	4.1779	2.8060	0.9179
	pre	2.8127	0.3704	0.4234	0.0916
	post $1$	5.0310	0.8505	0.6446	0.3392
	post $2$	9.2786	1.6789	1.3671	0.6084

Table 1: Validation results. For each of the three data sets (S1, S2, and S3), statistics are shown for the deformed image before registration, as well as the precontrast image and two post-contrast images after registration. The first three columns show maximum, mean, and standard deviation of displacement errors (in voxels). The last column shows the proportion of voxels with error exceeding one voxel.