Assessment

of

the fusion process

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INRIA

Virtual Physiological Human Project

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1. Introduction

Registering, or geometrically aligning images or volumes from the same or from different modalities is an important step in the analysis of medical images. Indeed, multiple images of patients acquired at different instants with different imaging facilities usually do not align i.e. corresponding structures are not positioned at the same location in all images.

Comparing and analysing the images at a given anatomical location is essential to asses the extent or the evolution of a disease. In this report, we compare two algorithms belonging to the two main classes of fusion approaches: geometric and iconic. The geometric approach consists in estimating local displacements of features and then fit a global transformation to those displacements while the iconic approach is based on the optimization over the space of transformation parameters of a similarity criterion computed on the entire image.

We chose to use Baladin algorithm as geometric approach because this algorithm is developed in our research laboratory, therefore we could have an easy access to it. Moreover, we unfortunately did not have another geometric algorithm proposed by another partner. An ITK based fusion algorithm was chosen as iconic approach because the Insight Toolkit (ITK) is widely used for the development of image segmentation and image fusion programs.

The assessment of the fusion process described in this document is a first step towards designing more robust, accurate and faster algorithms. It provides an evaluation framework that will later be used to assess the performance of the proposed algorithms.

In this report only rigid fusion is considered i.e. fusion that implies rigid transformations (consisting of only rotations and translations).

2. Fusion processes

2.1 ITK based fusion algorithm

In ITK, fusion is performed within a framework of components that can be easily plugged and interchanged, allowing users to select the tools most appropriate for their specific application.

For the ITK based fusion approach we designed, a 3D rigid transform using Euler angles was used with the Mattes mutual information (MI) metric, as implemented in ITK. The optimizer was Powell optimizer, with a maximum number of iterations set to 200, and the interpolation was performed with a linear interpolator.

2.2 Baladin fusion algorithm

Baladin algorithm is a block matching based approach [1]. It consists in extracting feature points in the two images (say the source and the target images) to be fused and in iterating the following steps until convergence:
1. To pair each feature point of the target image with the closest feature point in the source image.
2. To compute the transformation that will best match the paired points.
3. To discard blocks identified as outliers (which measured displacement is far from the current transformation estimation).

3. Methodology

Rigid body (3 rotations and 3 translations) fusion experiments were performed on one set of data. The set consisted of simulated BrainWeb[1] volumes (Montreal Neurological Institute) with 181×217×181 1-mm3 voxels. BrainWeb volumes are realistic simulations generated from real MRI data, and are used extensively in the neuroscience community for developing and validating segmentation and fusion algorithms.

The source image (Fig. 1) was a simulation of a normal T2 MRI volume without noise. The target (Fig. 2) was a normal T1 MRI brain volume without noise. Ground truth alignments were known for all data sets.

The experiments were divided into two successive phases.

- Phase I consisted in identifying the optimal parameters for each algorithm: the parameters that perform best on a heterogeneous dataset.
- Phase II aimed at determining the basin of convergence of these algorithms with the optimal parameters identified in phase 1.

[1] http://www.bic.mni.mcgill.ca/brainweb/

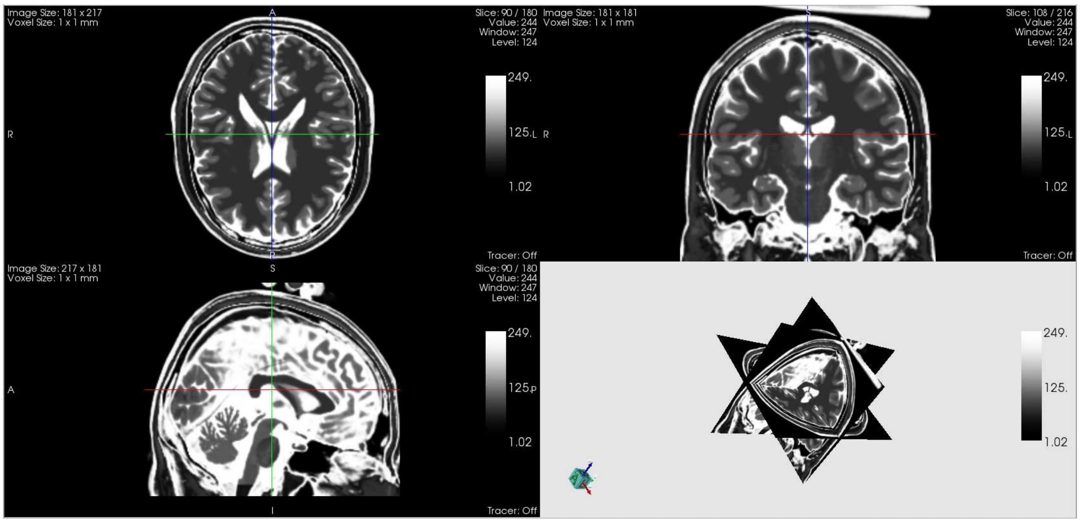

Figure 1. Source: BrainWeb T2 MRI volume, Normal, 0% noise

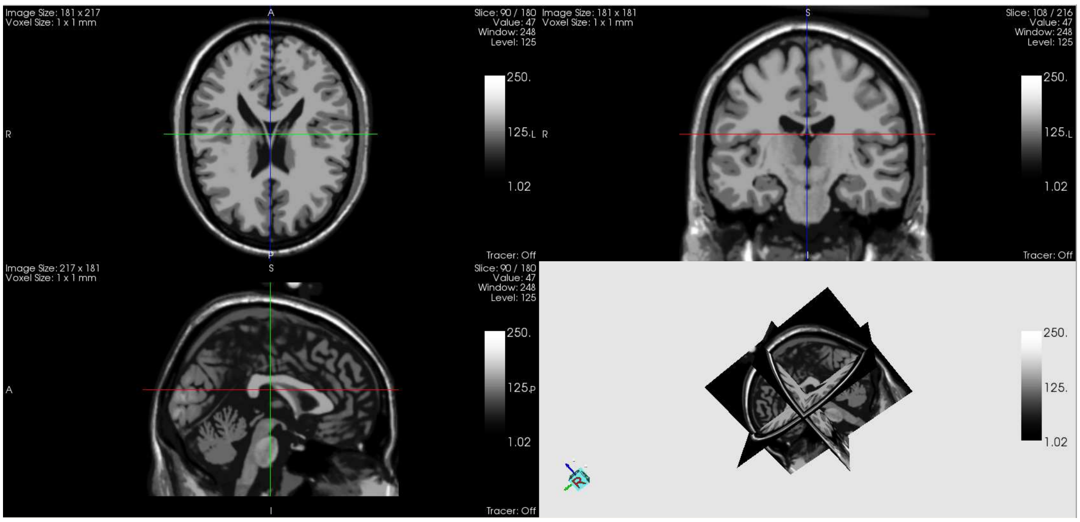

Figure 2. Target: BrainWeb T1 MRI volume, Normal, 0% noise

3.1 Experiments: Phase 1

For the first phase of experiments, 20 random images were generated by rotating, translating and adding noise to the T2 Brainweb image. Parameters were gradually chosen with an increasing degree of complexity:

- For each transformation indexed by i ($i \in [1;20]$) the three Euler angles (in degrees) Θ_x, Θ_y, Θ_z, were randomly chosen from interval $[-\frac{90*i}{20}; +\frac{90*i}{20}]$.
- Similarly, the three translation parameters (in mm) T_x, T_y, T_z, were randomly chosen from interval $[-\frac{Dim*i}{40}; \frac{Dim*i}{40}]$.

- And the level of Gaussian noise (σ) added was chosen in $[0; \frac{I_{MAX} * i}{20}]$.

The parameters for each transformation are summarized in Table 1.

This generated image was finally used as the source image to be fused with the target image, the T1 MRI Brainweb.

For the fusing process the following parameters varied:

- for ITK based algorithm, [25, 50, 100] histograms bins and [100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600, 51200, 102400, 204800, 409600, 819200] spatial samples.
- for Baladin algorithm, blocks of size [2, 3, 4] (mm), search window of size [1, 2, 4] (mm) were used, as well as [20, 40, 80] iterations.

Transformation Id	Θ_x (°)	Θ_y (°)	Θ_z (°)	T_x (mm)	T_y (mm)	T_z (mm)	σ
1	2.832513	3.652127	-3.357119	3.741051	1.436098	-3.642259	3.550852
2	0.843867	8.235123	8.367994	-6.197203	10.211863	8.274722	12.377079
3	8.107573	-9.669069	-2.112445	11.287220	9.511349	12.475219	25.082082
4	-16.714380	12.568655	15.623757	6.470213	11.185922	8.801395	20.003578
5	6.996505	-14.796599	9.272074	-21.184564	-12.101928	-20.535745	6.192151
6	17.466723	10.520746	-9.876628	24.447057	-30.307560	-3.326181	29.189222
7	16.727558	18.597594	-19.727026	-0.648426	-4.132728	9.268929	63.310811
8	18.337441	-16.126194	12.938593	11.229095	-29.285301	-27.584568	50.833133
9	37.239261	-12.928756	6.906688	-22.495518	24.536228	-19.947503	58.058572
10	17.916905	35.181293	41.336228	4.273005	-39.209248	-31.738892	32.832302
11	33.731008	-24.326064	31.114198	-25.532089	51.232613	-14.934116	27.572484
12	-26.882943	12.532825	-2.884804	-16.109778	43.073887	9.259680	84.107712
13	48.811659	-25.056835	30.092427	29.851228	-16.863113	7.979216	12.572848
14	-56.202285	3.880492	35.175071	54.989154	-56.217247	8.719958	83.786229
15	-65.893221	-21.988443	-45.605388	39.949126	-30.724752	3.873373	31.680320
16	14.685400	-34.132135	22.187390	27.398260	43.079117	-7.161577	17.099561
17	-41.466524	63.240616	-53.186163	50.126942	7.072262	76.330326	16.944546
18	-9.286120	-63.722251	74.827489	-80.695085	53.690014	51.688695	199.365435
19	-71.061470	-17.137167	-41.062161	51.596775	-14.139039	70.610854	44.052443
20	-42.515475	-63.802984	-65.507659	66.841890	17.295895	9.024697	36.963474

Table 1. Phase 1: Transformation parameters

3.2 Experiments: Phase 2

In the second phase of experiments, the best parameters identified during phase 1 were set for each algorithm. Then new fusion tests were run with initial misrotations along x axis (Θ_x) in [0, 5, 10, 15, 20, 25, 30] (in degrees), initial mistranslation along x axis (T_x) in [0, 15, 22, 30, 37, 45] (in mm), and with a level of noise (σ) in [0, 30, 45, 60, 75].

The objective of this second phase was to identify the basin of convergence of each algorithm.

As in phase 1, the transformed T2 MRI image was used as the source image to be fused with the T1 MRI target image.

4. Results

Fusion process performance was judged on the error between ground truth alignment and the transformation resulting from the fusion process.
For phase 1, execution times were also compared.

4.1 Phase 1

Results for phase 1 are shown in Figure 3 and Figure 4. This first phase permitted to determine the set of parameters that performed the best for each algorithm:

- the number of histograms bins and spatial samples used for the Mattes MI metric for the ITK based approach.
- the size of the blocks, the size of the search window and the number of iterations for Baladin algorithm.

The result of this was that:

- the best parameters for ITK based approach were:
  - 50 histograms bins.
  - 12800 spatial samples.
- the best parameters for Baladin algorithm were:
  - a block size of 4.
  - a search window size of 3.
  - 40 iterations.

Minimum execution times for each transformation were also recorded (Fig.4 (a) et (b)) to compare the speed of both algorithms.

All together 863 fusion experiments were performed with ITK based approach and 540 with Baladin algorithm.

As can be seen in Figures 4(a) and (b), ITK based algorithm is much faster than Baladin but less robust to large initial misrotation, mistranslation and noise, as seen in Figure 3.
As expected Figure 3 also shows that very large initial misalignment leads both algorithms to erratic convergence behaviour: a minimum fusion error higher than 50 mm.

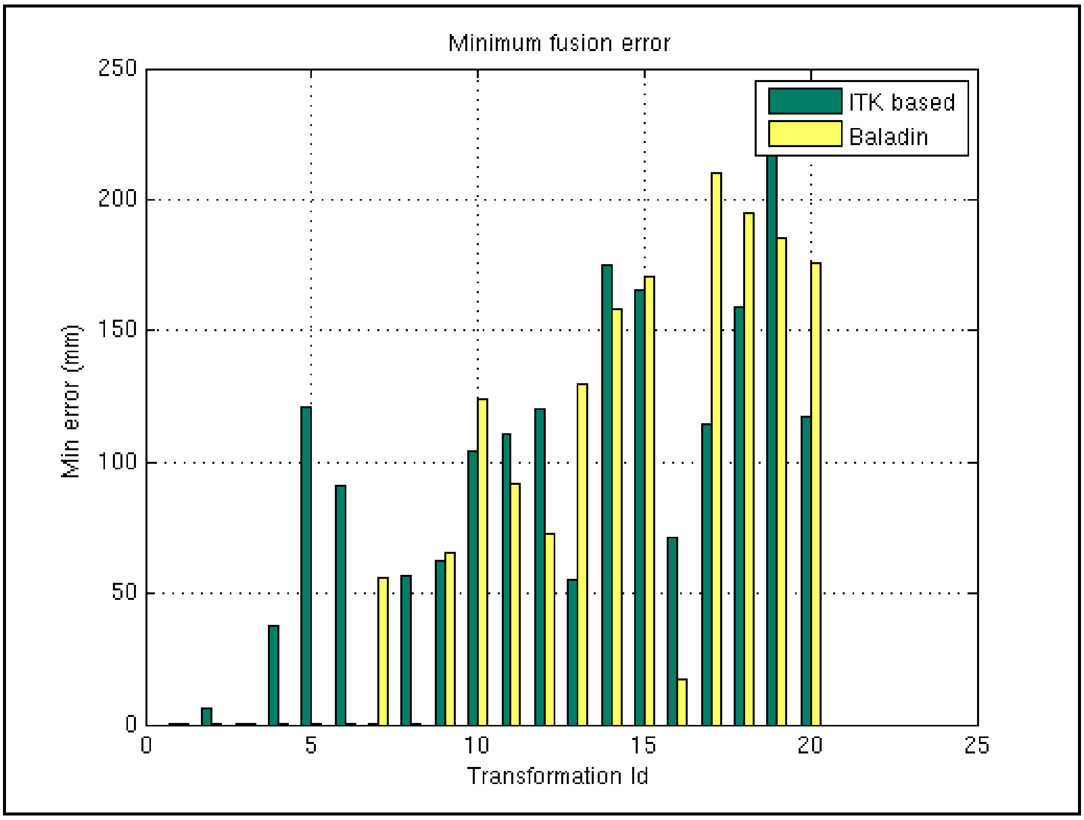

Figure 3. Minimum fusion error for each transformation

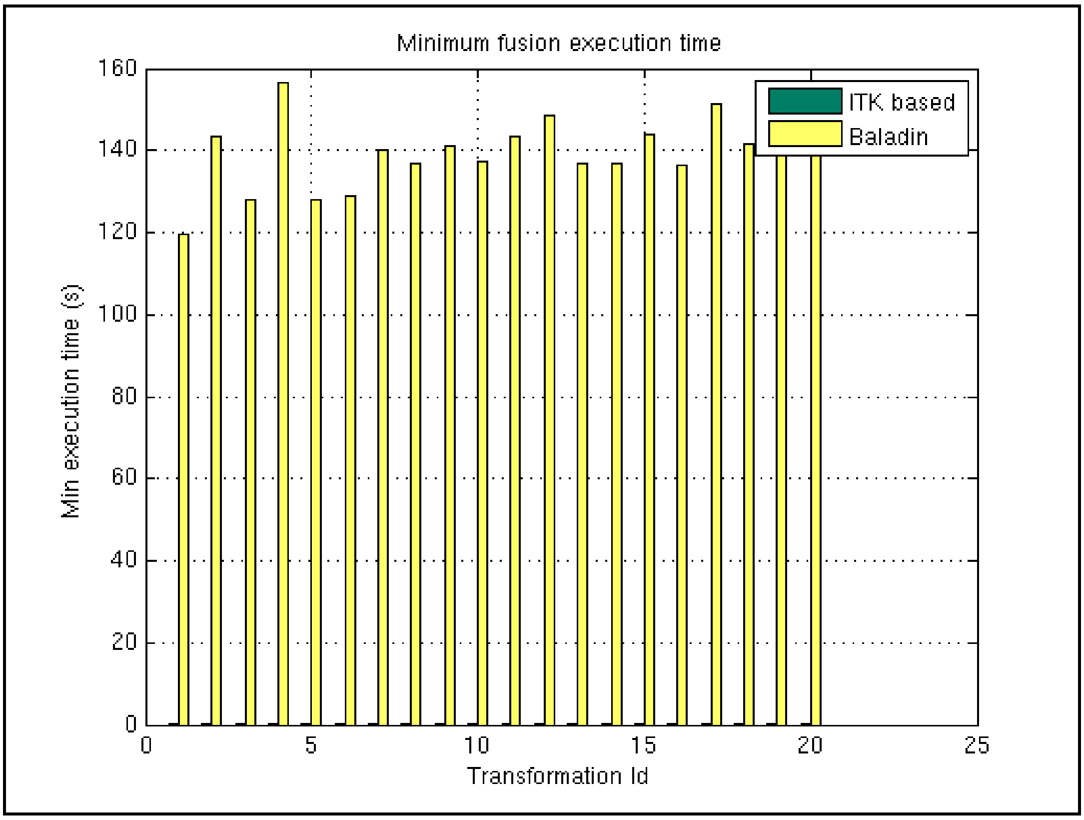

Figure 4(a). Minimum fusion execution time for each transformation

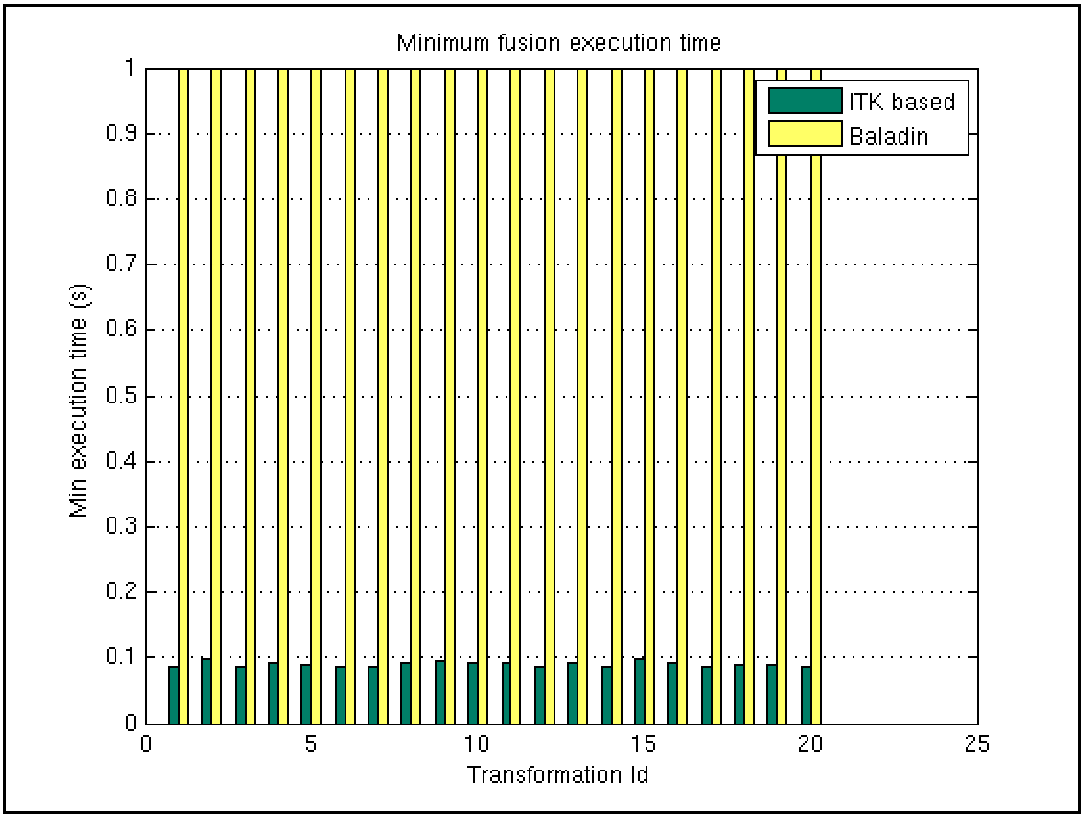

Figure 4(b). Minimum fusion execution time for each transformation (plot adapted to the scale of ITK based method results)

4.1 Phase 2

In phase 2, once the best parameter sets for each algorithm had been found, the objective was to identify their respective basins of convergence. Results for phase 2 are shown in Figure 5 and Figure 6.

In Figures 5(a) and (b) is displayed the fusion error against the rotation along x axis (in degrees) and against the translation along x axis (in mm) for ITK based approach, for σ = [30, 45].

Figures 6(a) and (b) display the same plot for Baladin algorithm.

All together 210 fusion experiments were performed for each approach.

As can be seen from Figures 5 and 6, Baladin algorithm has a larger basin of attraction than ITK based approach, for both σ = 30 and σ = 45. This shows that though slower Baladin algorithm is more robust to noise and initial misalignment than ITK based approach.

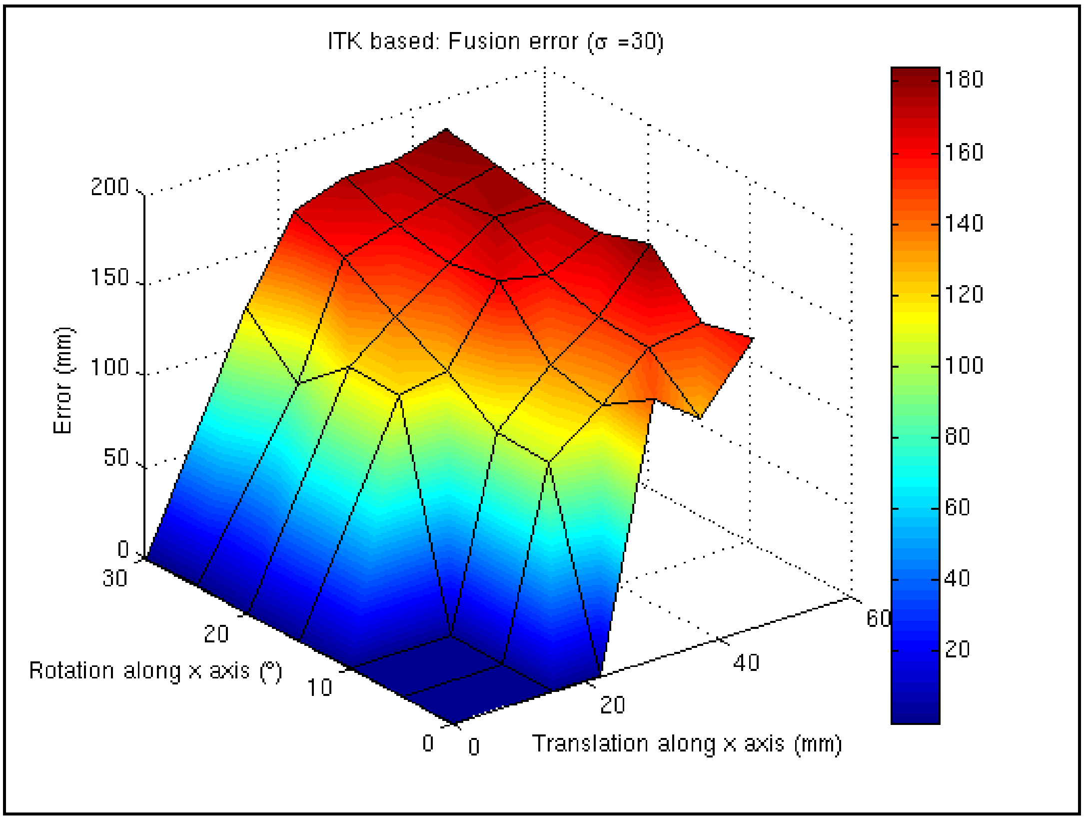

Figure 5(a). ITK based approach: Fusion error for σ=30

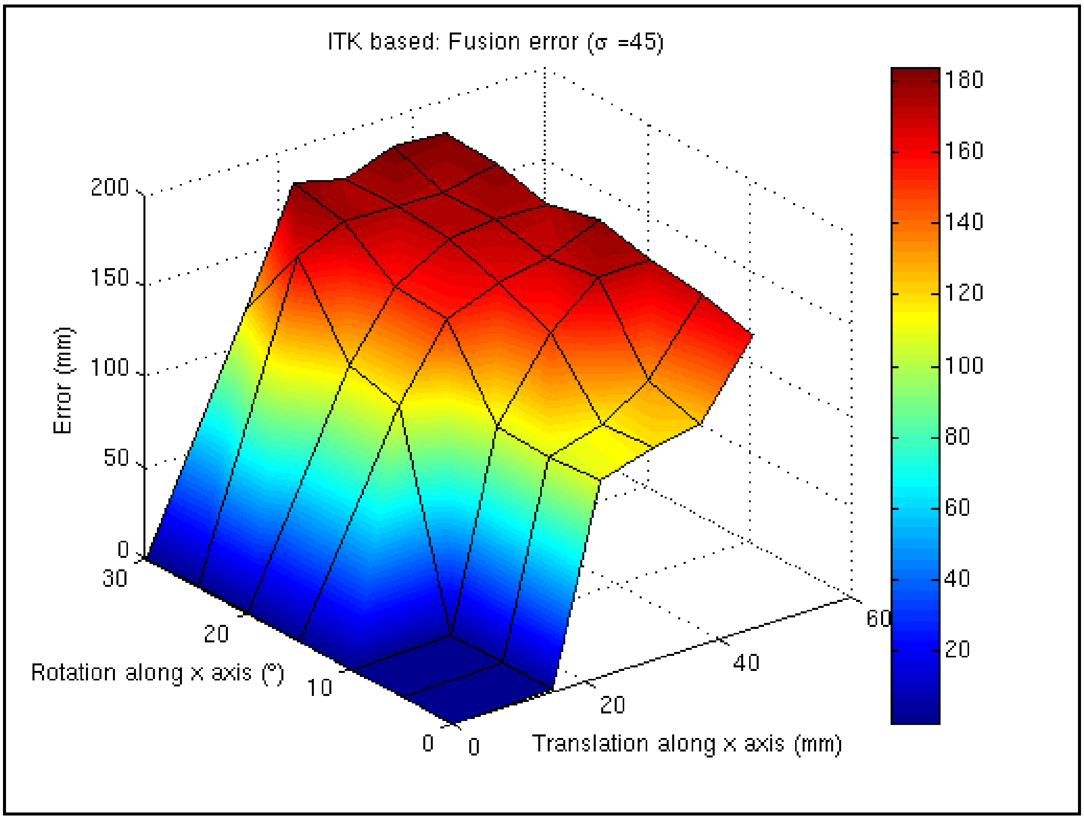

Figure 5(b). ITK based approach: Fusion error for σ=45

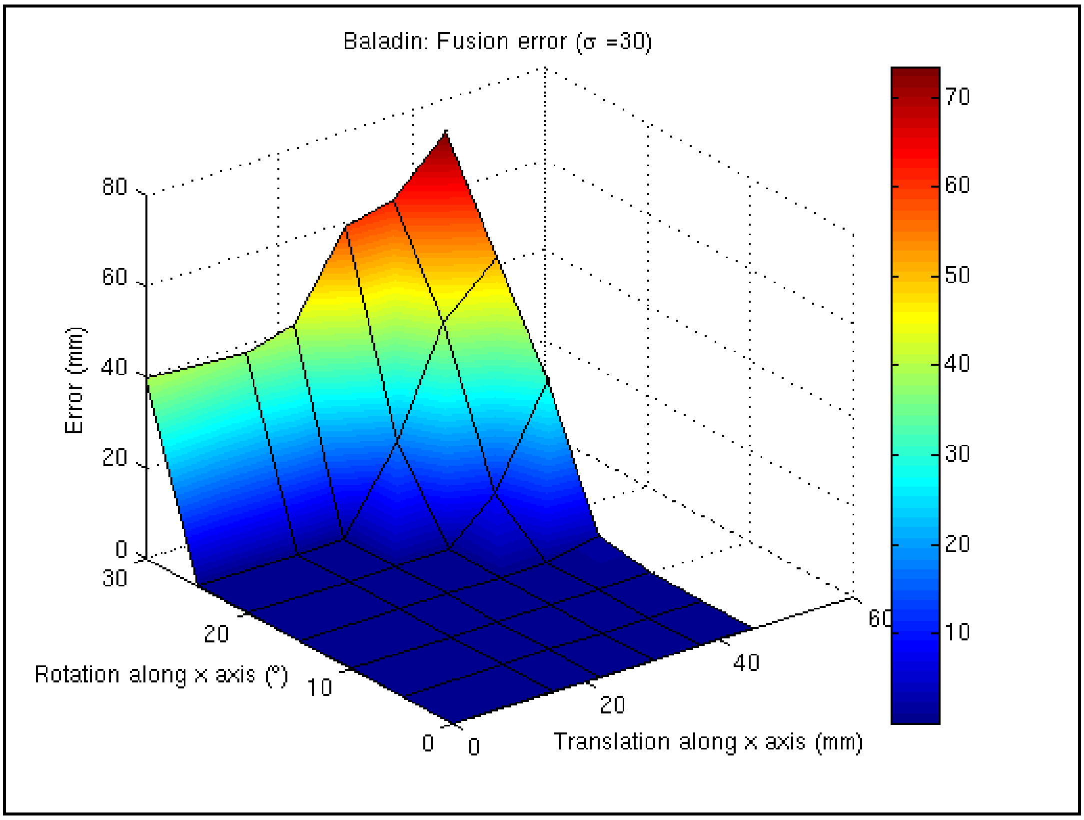

Figure 6(a). Baladin algorithm: Fusion error for σ=30

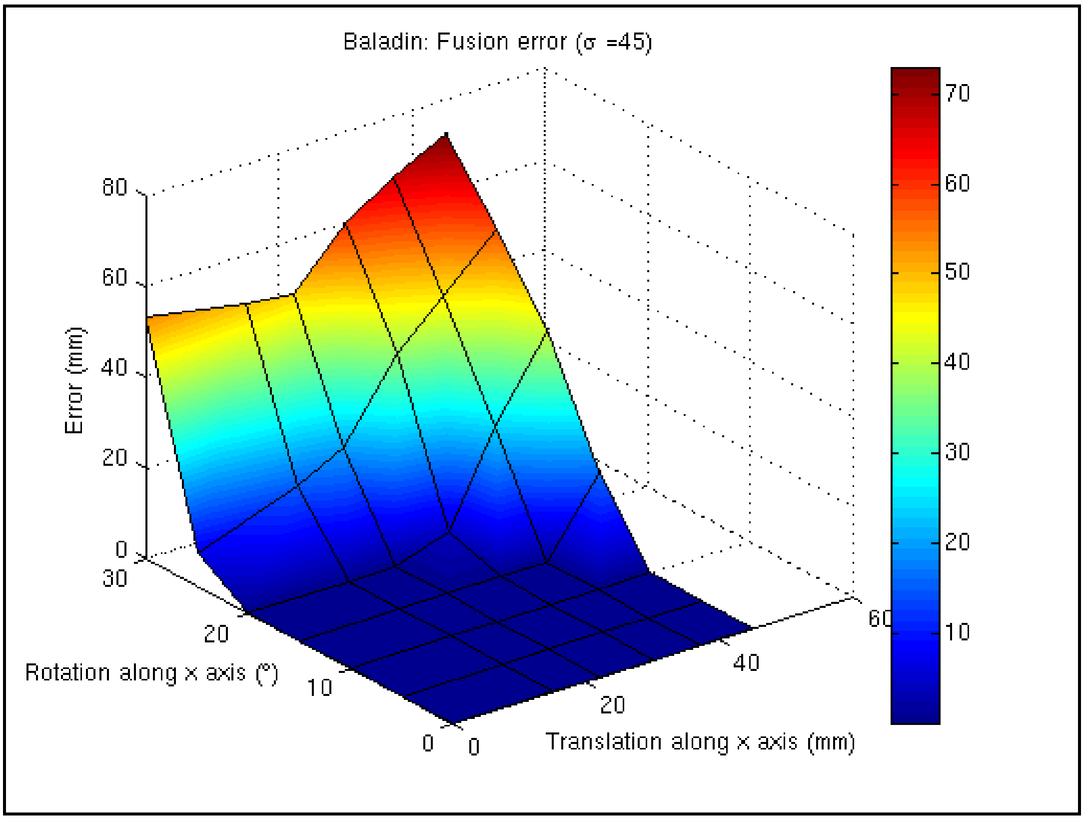

Figure 6(b). Baladin algorithm: Fusion error for σ=45

5. Conclusion

In this report we compared two algorithms belonging to two different classes of fusion approach: geometric (Baladin) and iconic (ITK). This work was divided into two successive steps:

- Step 1: Determine the fusion parameter sets that perform the best for each algorithm.
- Step 2: Identify the basin of convergence of each algorithm for the best parameter sets identified in phase 1.

It was shown that both approaches were lead to erratic convergence behaviour when the initial misalignment was very large. Baladin algorithm appeared slower than ITK based approach but more robust to noise and initial misalignment, its basin of convergence being larger than ITK's for the same set of misrotations, mistranslation and noise.

Future work will therefore include the design of more robust, accurate and faster algorithms. This report also provided a fusion process assessment framework that could be used as a basis to evaluate new fusion algorithms.

References

[1] S. Ourselin, A. Roche, S. Prima, and N. Ayache. Block Matching: A General Framework to Improve Robustness of Rigid Registration of Medical Images. In A.M. DiGioia and S. Delp, editors, *Third International Conference on Medical Robotics, Imaging And Computer Assisted Surgery (MICCAI 2000)*, volume 1935 of *Lectures Notes in Computer Science*, Pittsburgh, Penn, USA, pages 557-566, octobre 11-14 2000. Springer.