Assessment

# of the fusion process

with

NewUOA algorithm

Version 1.0

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 developed an ITK implementation of an optimisation method introduced by Powell and called NEWUOA and chose this implementation as another iconic approach to assess.

This report complements the assessment of the fusion process described in a previous document (cf. Deliverable 7.3 of the VPH-NoE project) and will thus compare Baladin, ITK based and NEWUOA algorithms.

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

2. Fusion process

2.1 NEWUOA algorithm

The image registration process, based on the intensities of the images requires a system that allows the computation of the optimal parameters. In registration procedures, derivative-free optimisation methods are often employed for this task. In this report, a recent derivative-free optimisation algorithm, called NEWUOA (NEW Unconstrained Optimisation Algorithm) is assessed.
Modern optimisation algorithms often use a local model of the objective function F. According to Powell [1] the original idea is from Winfield (1973) [2] who created a quadratic model Q of the objective function F. In such case the model Q is built to fit F, and the optimum of Q is considered to match the one of F. With a non quadratic function, this is not true, so the model Q is updated with the value of F corresponding to the previous

optimum of Q, and some iteration is performed until a stopping criterion is reached.

In 2000, Powell proposed an implementation of this approach termed Unconstrained Optimisation BY Quadratic Approximation (UOBYQA) [1] which is the basis on which NEWUOA is constructed. The quadratic model Q is created using m sample points of F. A standard quadratic interpolation of a function requires $m = \frac{1}{2}(n+1)(n+2)$ samples for a problem of dimension n. A point x0 is the initial parameter provided by the user; for our rigid registration case this is the identity transformation. Interpolation points are selected inside a neighbourhood of x0. This neighbourhood is called the trust-region. The point xnew is the optimal point computed inside the trust-region. The algorithm updates Q by selecting the interpolation point xmove that is the farthest from the point xnew. The point xmove is replaced by xnew and Q is updated with the value of F (xnew). The trust-region radius decreases during the optimisation process when the optimum of Q stops decreasing the value of F. The iterations stop either when the trust-region radius reaches a user-defined final radius or when Q is considered close enough to F.

NEWUOA uses the same method as UOBYQA, but one important speed factor of NEWUOA is the number of samples of the function F used for the creation of Q. As stated before, the required number of interpolation point required for a perfect modelling of a quadratic model is exactly $m = \frac{1}{2}(n+1)(n+2)$. The initial construction of Q is possible with less samples of F thanks to additional constraints on the first and second derivatives of Q. Reducing the number of calls of the objective function F speeds up the algorithm. NEWUOA usually shows good behaviour for optimisation when the number of samples is selected as $m = 2n+1$, which is one of the values used for the following experiments.

Finally the algorithm can be summarised as:

- Create an initial quadratic model Q of the function to optimise F,
- Do the following iterations:
    - Compute the minimum of Q inside a trust-region,
    - Improve the model using the latest optimum,
    - Stop if the latest trust-region is lower than the user-defined end value,
    - Stop if the distance between Q and F is small enough (perfect match of the model and the objective function F),
    - Decrease the trust-region radius, if the values computed for F stop decreasing.

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.

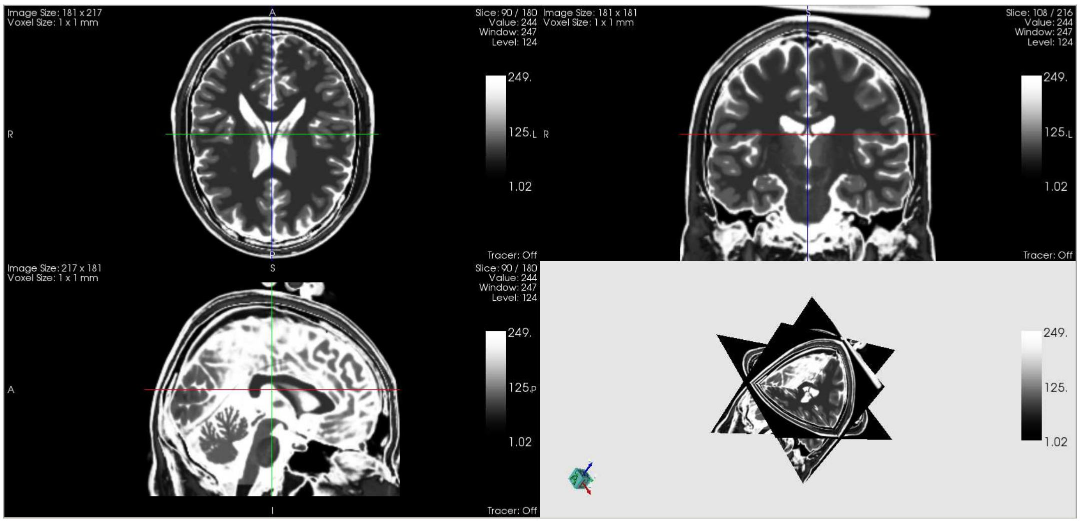

Figure 1. Source: BrainWeb T2 MRI volume, Normal, 0% noise

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

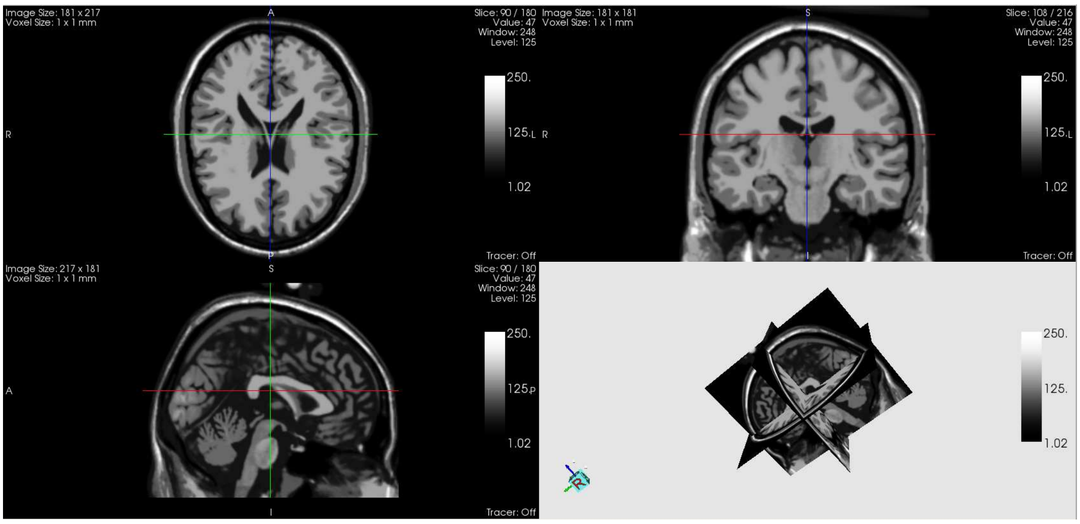

Figure 2. Target: BrainWeb T1 MRI volume, Normal, 0% noise

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 $[-\frac{90*i}{40}; +\frac{90*i}{40}]$.
- 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.

Transformation Id	Θ_x (°)	Θ_y (°)	Θ_z (°)	T_x (mm)	T_y (mm)	T_z (mm)	σ
1	1.254610	-0.344462	-1.841295	-1.056717	-1.878912	-0.990951	2.805543
2	0.244285	-0.383181	3.378344	0.163372	4.813305	1.246267	12.210598
3	-3.500455	2.377651	-2.847628	2.332296	3.175912	-5.864498	4.872862
4	-4.967279	3.020989	6.199059	-2.815230	6.087276	3.173510	0.171241
5	2.298836	-2.547648	9.359803	-11.286457	-1.018567	-1.711603	14.691709
6	7.294313	-4.793261	7.687961	-0.777653	-15.110923	-8.800010	27.607245

7	-0.835191	-10.939282	-5.004575	3.401553	-11.705974	7.552170	10.837163
8	15.027276	-8.313783	9.558001	-11.270436	-9.222579	-14.801693	29.386678
9	7.426211	1.887021	-3.007982	5.882432	7.207431	7.290457	36.478263
10	20.032835	-13.097928	9.417677	-11.935566	-20.647754	4.855503	28.696278
11	-2.043088	8.016265	13.379133	-7.455398	9.667923	-4.173206	59.040282
12	17.977508	-13.152186	6.126880	4.466130	2.652131	20.087798	20.255596
13	-10.642667	-22.275949	25.730024	8.562089	-1.448356	8.195320	45.143348
14	9.280623	2.764814	13.925937	1.425078	37.496866	-17.821835	9.442496
15	-26.345421	-29.457582	-6.440850	-3.504189	-10.919209	17.885377	60.042591
16	19.582588	31.165457	34.037341	-22.297148	-31.345719	14.209683	9.569643
17	1.943437	2.321333	27.627196	-1.165157	-9.825987	13.187340	80.333830
18	1.624250	-12.335274	-28.350222	7.012199	-23.226510	-37.104214	86.628592
19	-21.991852	-4.924602	16.056565	-12.102855	24.360753	-9.052525	82.778747
20	18.364269	-5.192513	-43.238014	-15.307362	-8.212420	-20.790527	25.124359

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 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.
- the best parameters for NewUOA algorithm were:
  - nbHistBins = 256
  - nbSpatialSamples = 100000
  - rhobeg = 0.3142
  - rhoend = 0.01

Minimum execution times for each transformation were also recorded (Fig.4).

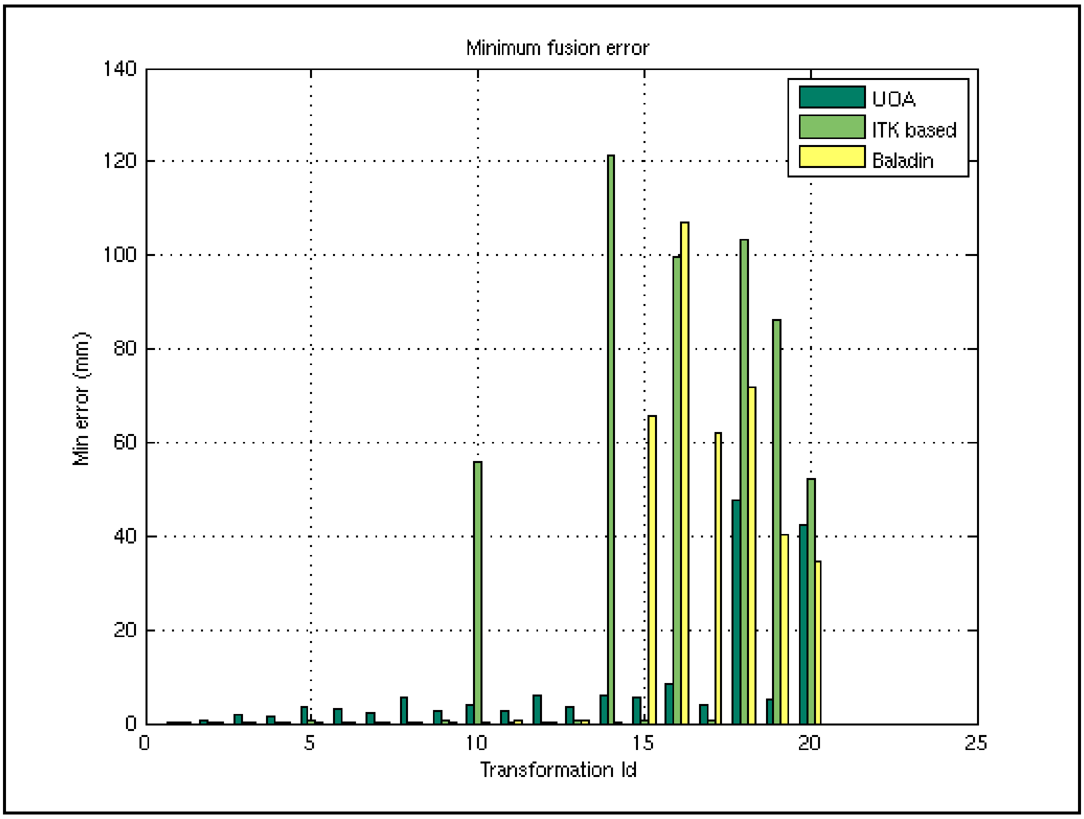

Figure 3. Minimum fusion error for each transformation

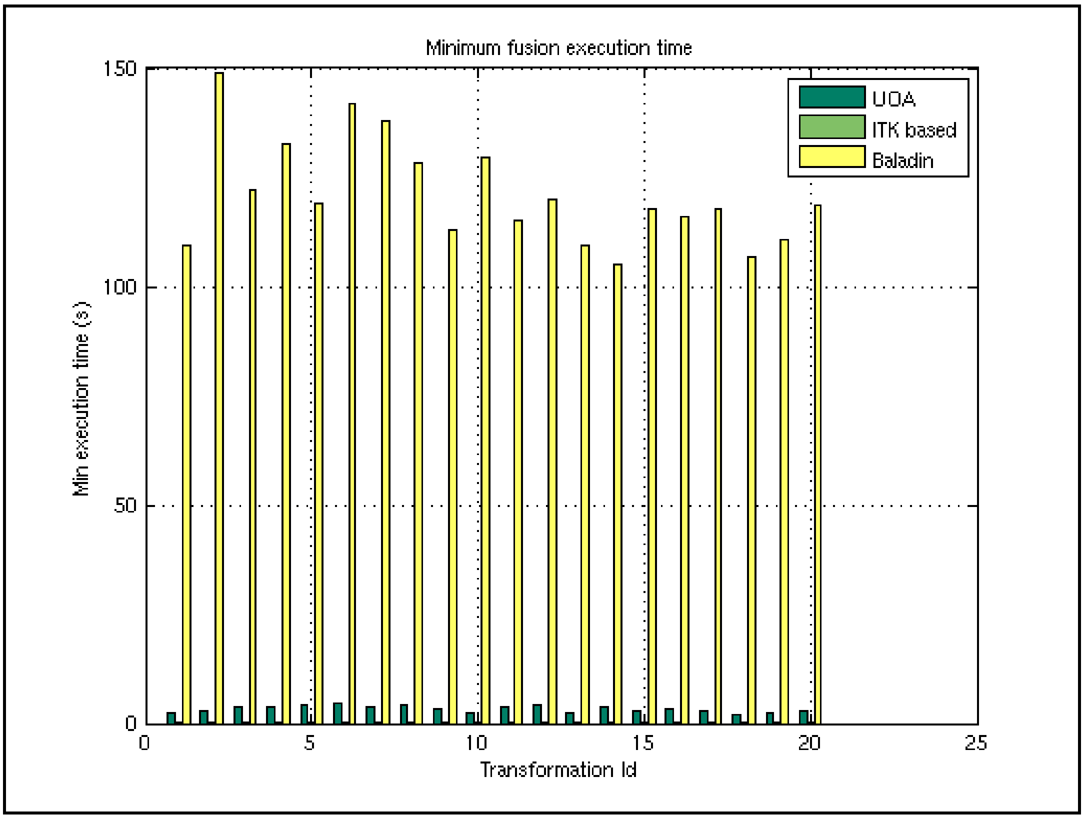

Figure 4. Minimum fusion execution time for each transformation

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, Figure 6 and Figure 7.

In Figures 5,6 and 7 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.

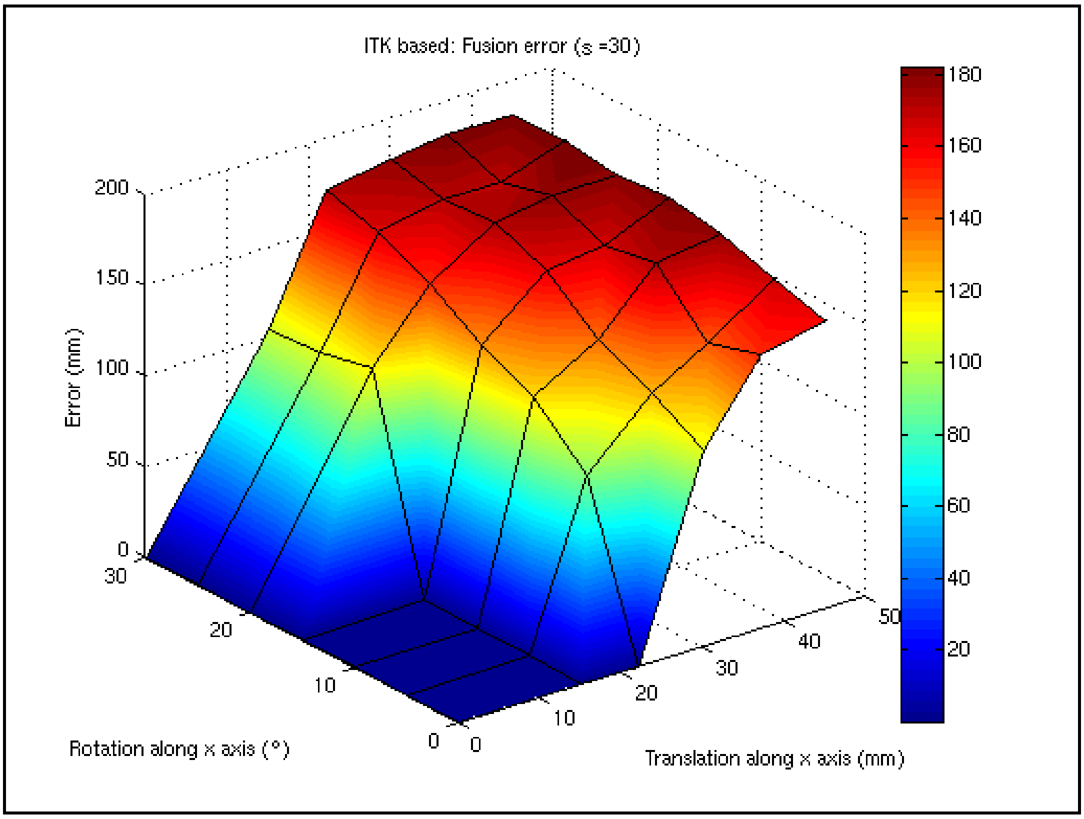

Figure 5. ITK based approach: Fusion error for σ=30

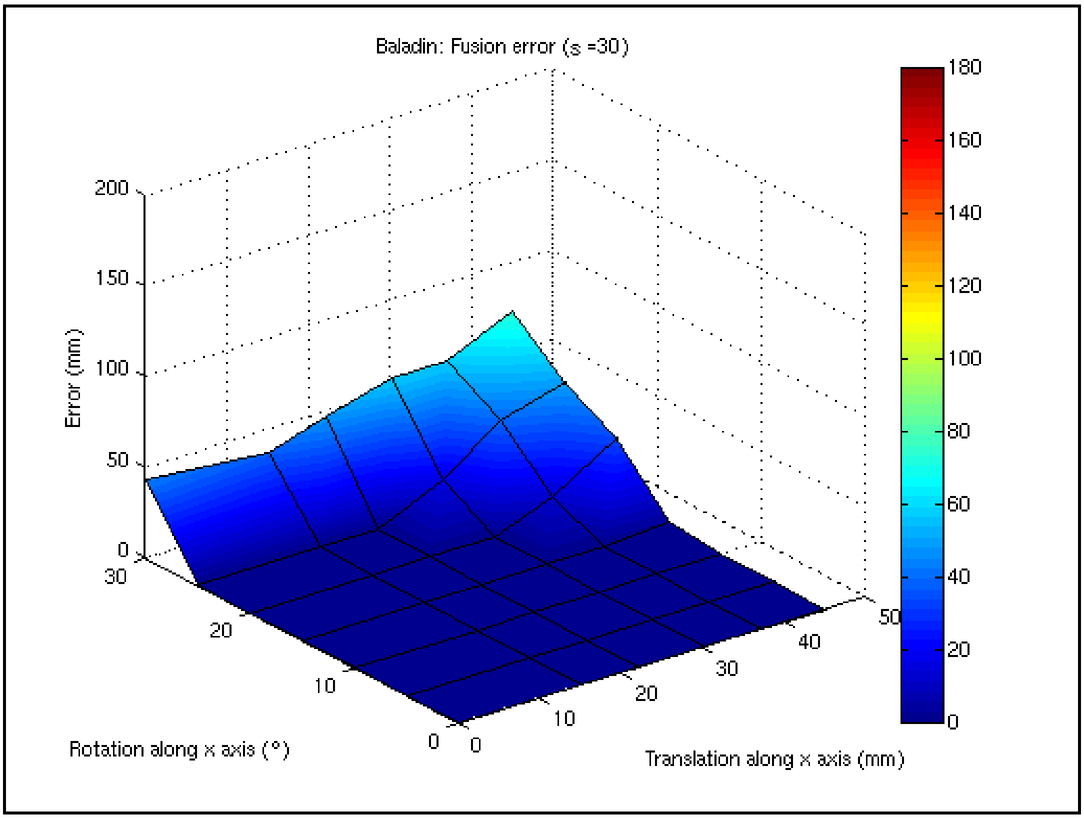

Figure 6. Baladin algorithm: Fusion error for σ=30

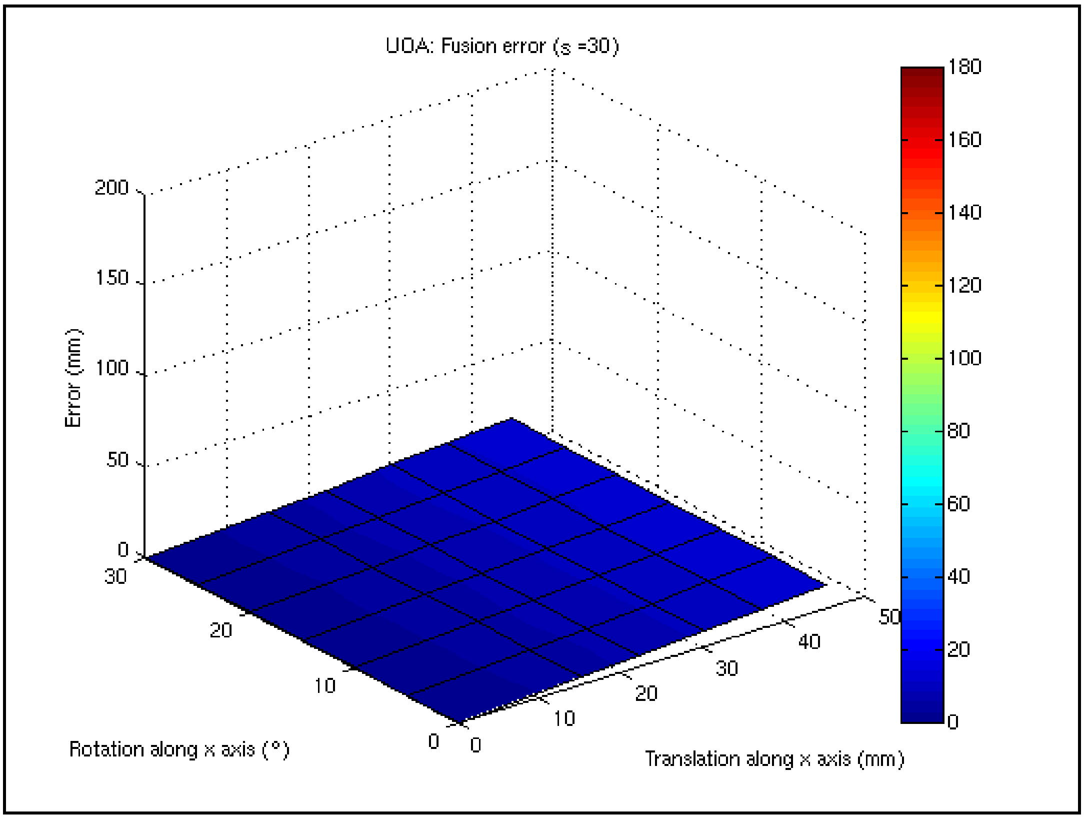

Figure 7. Baladin algorithm: Fusion error for σ=30

5. Scripts

The scripts are organised as follows:

- In ‘scripts/cluster’ there are 2 directories (phase 1 and phase 2 corresponding to the two phases of experiments). Those scripts are meant for internal use on INRIA’s cluster.
    - README file explains how to use and launch the scripts
    - RegParam.py generates the different parameters sets to be tested.
    - qsubCommand.pbs is called by RegParam.py and takes care of sending the process to a node on the cluster.
    - RegProcess.py (called by qsubCommand.pbs) takes care of the registration process.

- In ‘scripts/matlab’ there are 2 directories (phase 1 and phase 2 corresponding to the two phases of experiments). Those scripts take care of results analysis.

- computeCornerDisplacements.m takes a transformation matrix M as input and compute the displacement of the eight corners of the 3D volume.
- itkMat2BaladinMat.m takes a ITK matrix M as input an convert it into a Baladin transformation matrix.
- computeDisplacements.m takes the transformation matrix and computes the corresponding real displacements.
- computeErrors.m takes care of computing of the registration errors.
- plotMinErrors.m plot the minimal registration errors computed.

NOTE: All scripts are commented and it is indicated where to put paths to results files.

References

[1] M. Powell, "UOBYQA: unconstrained optimization by quadratic approximation," tech. rep., Department of Applied Mathematics and Theoretical Physics, University of Cambdrige, 2000.

[2] D. Winfield, "Function minimisation by interpolation in a data table," J. Inst. Maths Applics, 1973.