An Adaptive Physics-Based Non-Rigid Registration Framework for Brain Tumor Resection

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Keywords: non-rigid registration, biomechanical model, tumor resection, ITK, Finite Element Method

Abstract

We present an Adaptive Physics-Based Non-Rigid Registration (APBNRR) framework for warping pre-operative to intra-operative brain Magnetic Resonance Images (MRI) of patients who have undergone a tumor resection. The proposed method, iteratively removes the tumor from a gradually warped segmented pre-operative image via an adaptively changing biomechanical model which is necessary for dealing with deformations like those induced by a tumor resection. We show that our scheme not only accurately captures the deformations associated with the resection but also satisfies the time constraints imposed by the neurosurgical workflow. We evaluate the APBNRR framework on clinical volume MRI data and compare it with the publicly available PBNRR method of ITK. In all the case studies, our method achieves high accuracy and close to real-time performance. Indeed, APBNRR reduces the alignment error up to 6.61 and 4.95 times compared to a rigid and the PBNRR registration, respectively, while the execution time is less than 1 minute in a Linux Dell workstation with 12 Intel Xeon 3.47GHz CPU cores and 96 GB of RAM.

1. INTRODUCTION

Non-Rigid Registration between pre-operative MRI data and the in-situ shape of the brain can compensate for brain deformation during Image-Guided Neurosurgery (IGNS). Non-Rigid Registration (NRR) is a key enabling technology which brings real-time information that the surgeon is otherwise unable to collect intra-operatively.

In [1, 13] it was demonstrated that a reasonably accurate NRR of pre-operatively acquired MRI can be achieved well, within the time constraints imposed by the neurosurgical procedure, using intra-operative data. Methods [1, 4, 7] compensate for small brain deformations (shifts) caused mainly from the cerebro spinal fluid (CSF) leakage, gravity, edema and administration of osmotic diuretics. However, the complex neurosurgical procedure of brain retraction or tumor resection, which invalidates the biomechanical model defined on the pre-operative MRI and compromises the fidelity of the IGNS, is not addressed. In this paper we focus in one of those two challenges: the tumor resection.

In [8], the retraction and the resection were simulated to update the pre-operative image to realistically reflect the brain morphology in the Operating-Room (OR). A Finite Element (FE) model was created and boundary conditions were applied to the retracted surfaces. Then, the elements that coincided with the intra-operatively resected tissue were manually deleted.

In [10], an adaptive FE multi-level grid registration method which accommodates a superficial tumor resection was developed. This method evaluated only in 2D medical and synthetic images. In [9], a robust Expectation-Maximization (EM) framework was presented to simultaneously segment and register a pair of 3D clinical images with partial or missing data. A MatLab implementation of this method required 30 min to register a pair of $64 \times 64 \times 64$ volumes on a 2.8 GHz Linux machine.

In this paper, we augment the software implementation in [7] and propose an Adaptive Physics-Based Non-Rigid Registration (APBNRR) framework to compensate for the brain deformation induced by a tumor resection. The proposed scheme removes automatically the tumor from a gradually warped segmented pre-operative image, while an adaptive biomechanical model deals with the complex brain deformations occurring during the resection. Our method is reasonably fast to satisfy the time constraints required by the neurosurgical procedure. We introduce several parallel components, thus we can register adult brain MRIs with resolution $250 \times 219 \times 176$ voxels in less than 60 seconds. The evaluation of our framework is based on 6 volume clinical cases with : (i) brain shifts (2 cases), (ii) partial tumor resections (2 cases) and (iii) complete tumor resections (2 cases). In all the case studies, the APBNRR achieves higher accuracy compared to the publicly available non-rigid registration method PBNRR [7] of ITK[1] and exhibits close to real-time performance.

In the next section we will describe the proposed scheme that manages the FE model adaptivity. A comprehensive description of the framework with an extensive evaluation on a larger data set is available at [6].

[1] http://www.itk.org/

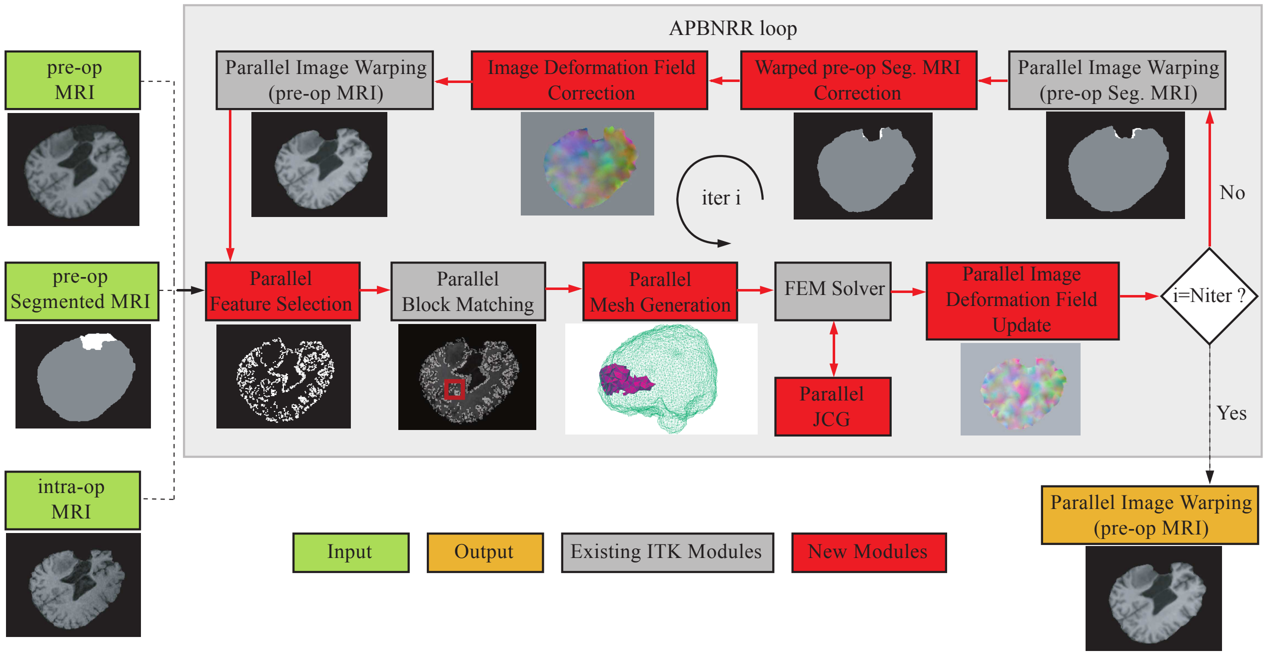


Figure 1. The APBNRR framework [6]. The green, red and gray boxes represent the input, the new contributions and the existing ITK modules, respectively. The red arrows show the execution order of the modules. Orange represents the output warped pre-operative MRI.

2. METHOD

The APBNRR framework is built on the ITK open-source system. Figure 1 illustrates the modules of the framework. All parallel modules are developed with the POSIX thread library.

The basic idea of the APBNRR method is to iteratively estimate a dense deformation field that defines a transformation for every point in the intra-operative to the pre-operative image. The estimation of the dense field is facilitated by a heterogeneous (brain parenchyma, tumor) FE biomechanical model of high quality tetrahedral elements. During the execution, the model deforms and adapts to the new brain morphology induced by the tumor resection (Figure 1).

In each APBNRR iteration, first we select high discriminant features (blocks) from the warped pre-operative MRI (when $i = 1$ the warped pre-operative MRI equals to the input pre-operative MRI). Then, we compute a sparse displacement field that matches the selected features to their corresponding blocks in the intra-operative MRI (block matching displacements). Next, we apply the sparse field of matches to the model and we estimate the deformations on the mesh vertices with the solution of a linear system of equations. The model stiffness and consequently the computed mesh deformations mostly depend on: a) the mechanical properties of the brain and tumor tissues, b) the shape (quality) of the elements, c) the number and the positions of the selected blocks, d) the block matching displacements.

In a later step, we convert the mesh deformations to an image deformation field which is used to warp the pre-operative and the segmented pre-operative images. Additionally, we apply correction modules on the image deformation field and the warped segmented pre-operative image, to compensate for the resected tissue (Figure 1). We should point out that the image deformation field is additive; it holds the sum of the previous image fields at iterations $1, 2, \ldots, i-1$ and the current image field at iteration i. In that way, independently of the number of iterations, we interpolate only the input pre-operative and segmented pre-operative images.

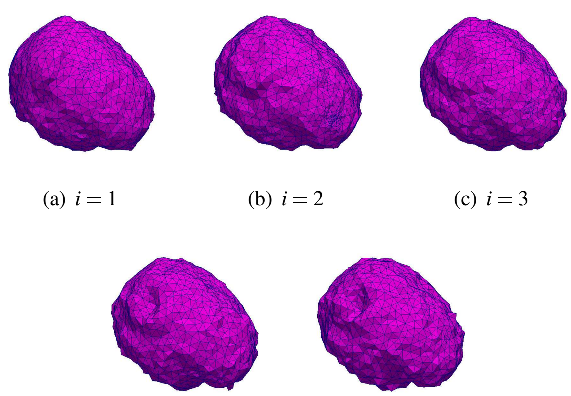
Figure 2 shows the FE brain model adaptivity implemented on the APBNRR framework. The example consists of five adaptive iterations. For each mesh: a) its surface is conformed to the segmented image boundary of the current iteration i, and b) the distorted poor quality tetrahedral elements occurring after each deformation are eliminated.

The model deformation and consequently the image warping, stops when $i = Niter$, where $Niter$ is the desired number of adaptive iterations (Table 2). Our experimental evaluation has shown that a satisfactory alignment accuracy can be achieved within the neurosurgical time constraints, when $Niter = 3-5$.

The output registered image is the warped pre-operative MRI at iteration $Niter$ (Figure 1). A complete description of the new and existing APBNRR modules can be found in [6, 7].

Table 2. The input parameters for the 6 clinical cases. BS : Brain Shift, PTR : Partial Tumor Resection, CTR : Complete Tumor Resection, FS : Feature Selection, BM : Block Matching, MG : Mesh Generation, FEMS : FEM Solver, All : PBNRR-APBNRR, x : axial, y : coronal, z : sagittal.

Parameter	Units	Value	Description	Module	Method
$B_{s_x} \times B_{s_y} \times B_{s_z}$	voxels	$3 \times 3 \times 3$	Block size	FS-BM	All
$W_{s_x} \times W_{s_y} \times W_{s_z}$	voxels	$7 \times 7 \times 7$ (BS) $9 \times 9 \times 9$ (PTR, CTR)	Window search size	BM	All
F_s	-	5%	% of selected feature blocks	FS	All
δ	-	5	Mesh size	MG	APBNRR
E_b	Pa	2.1×10^3	Brain Young's modulus	FEMS	All
E_t	Pa	2.1×10^4	Tumor Young's modulus	FEMS	APBNRR
ν_b	-	0.45	Brain Poisson's ratio	FEMS	All
ν_t	-	0.45	Tumor Poisson's ratio	FEMS	APBNRR
λ	-	1	Trade off parameter	FEMS	All
F_r	-	25%	% of rejected outlier blocks	FEMS	All
N_{appr}	-	10	Number of approximation steps	FEMS	All
N_{int}	-	5	Number of interpolation steps	FEMS	All
N_{iter}	-	3 (BS) 4 (PTR,CTR)	Number of adaptive iterations	-	APBNRR



(a) $i = 1$ (b) $i = 2$ (c) $i = 3$ (d) $i = 4$ (e) $i = 5$

Figure 2. The adaptive FE biomechanical model implemented in the APBNRR framework. Each mesh is conformed to the warped segmented pre-operative image of iteration i. Number of generated tetrahedra for $i = 1 - 5$: $7725, 8102, 7720, 7262, 6991$.

3. RESULTS

We evaluate our framework on 6 clinical volume MRI cases and we compare it with the publicly available non-rigid registration method PBNRR [7] of ITK. Prior to the non-rigid registration we extract the brain from the skull with BET [11] and we rigidly align the pre-operative to the intra-operative MRI with 3D Slicer[1]. All MRI data are anonymized and an Institutional Review Board (IRB) is granted. The Surgical Planning Laboratory at Brigham and Women's Hospital [12] provided the first three cases and the Department of Neurosurgery at Shanghai Huashan Hospital provided the last three [3]. Depending on the type of resection depicted in the intra-operative MRI (i.e., just brain shift but no tumor resection, or partially/completed resected), the cases are categorized as Brain Shifts (BS), Partial Tumor Resections (PTR) and Complete Tumor Resections (CTR). From totally 6 cases, 2 are BS, 2 are PTR and 2 are CTR. Table 1 lists the provided clinical data. All MRI data were resampled to a uniform image spacing $1.00 \times 1.00 \times 1.00$ (mm) along the x, y, z (axial, coronal, sagittal) image directions. For all the conducted experiments we used linear displacement FE biomechanical models with 4-node tetrahedral elements and the tissues (brain parenchyma, tumor) were modeled as elastic isotropic materials. Table 2 lists the parameters for the experiments. More details about the parameters are given in [6, 7].

[1] http://www.slicer.org/

Table 1. The clinical MRI data of this study. BS : Brain Shift, PTR : Partial Tumor Resection, CTR : Complete Tumor Resection.

Case	Type	Provider	Genre	Tumor Location
1	BS	B&W	M	R frontal
2	BS	B&W	F	R occipital
3	PTR	B&W	F	L frontal
4	PTR	Huashan	M	L frontal
5	CTR	Huashan	M	R temporal
6	CTR	Huashan	F	L posterior temporal

3.1. Quantitative evaluation

For the quantitative evaluation, we employ the Hausdorff Distance (HD) metric as it is implemented in [5].

The HD is computed between extracted point sets in the warped pre-operative and the intra-operative images. For the point extraction we employ ITK's Canny edge detection method [2]. We compute the alignment errors HD_{RIGID}, HD_{PBNRR} and HD_{APBNRR}, after a rigid, a non-rigid (PBNRR) and an adaptive non-rigid (APBNRR) registration, respectively. The smaller the HD value, the better the alignment. Additionally, we compute the alignment improvement of the APBNRR compared to the rigid and the PBNRR registration. The corresponding ratios are HD_{RIGID}/HD_{APBNRR} and HD_{PBNRR}/HD_{APBNRR}. When ratio > 1 the APBNRR outperforms the other method. The higher the ratio, the greater the improvement.

In Table 3 we present the quantitative results. Figure 3 depicts all HD values and their corresponding average values for all the experiments. As shown in Table 3 and Figure 3, our method, in all the case studies, significantly reduces the alignment error compared to the rigid and the PBNRR registration. The maximum improvement occurs in case 5 (CTR), with values 6.61 and 4.95, respectively (Table 3). On the average the APBNRR is 4.23 and 3.18 times more accurate than the rigid and the PBNRR registration, respectively (Table 3). Generally, the APBNRR performs better on the PTR and CTR cases, because it captures accurately the large, complex intra-operative deformations associated with the tissue resection. On the other hand, the PBNRR is a non-adaptive method which is designed to handle only the small brain shifts occurring during the surgery.

Table 3. The quantitative evaluation results for the 6 clinical cases. $HD_{RIGID}, HD_{PBNRR}, HD_{APBNRR}$ is the alignment error after a rigid, a non-rigid (PBNRR) and an adaptive non-rigid registration (APBNRR), respectively. All HD are in mm.

Case	HD_{RIGID}	HD_{PBNRR}	HD_{APBNRR}	$\frac{HD_{RIGID}}{HD_{APBNRR}}$	$\frac{HD_{PBNRR}}{HD_{APBNRR}}$
1	13.63	11.22	5.91	2.30	1.89
2	8.60	7.00	5.38	1.59	1.30
3	19.33	16.03	3.74	5.16	4.28
4	12.72	9.43	2.82	4.51	3.34
5	16.15	12.08	2.44	6.61	4.95
6	19.62	12.53	3.74	5.24	3.35
Average	15.00	11.38	4.00	4.23	3.18

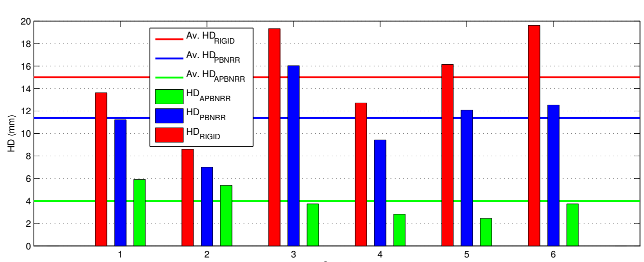


Figure 3. The Hausdorff Distance (HD) error for the 6 clinical cases. The horizontal lines illustrate the average HD error.

3.2. Qualitative evaluation

Figure 4 depicts the qualitative results for cases PTR (3-4) and CTR (5-6). These cases clearly demonstrate the impact of our method on the challenging problem of tumor resection. Figure 4 shows the same representative slice for all the MRI belonging to the same row. The cyan color delineates the tumor segmentation in the pre-operative image. The fifth and sixth column (from the left) show the warped pre-operative MRI subtracted from the intra-operative MRI. The black and white regions in the difference images indicate larger discrepancies, while the gray regions indicate smaller discrepancies. Obviously, the APBNRR aligns the images with high accuracy, particularly near the tumor resection margins where the black and white regions are mostly eliminated. Moreover, the APBNRR provides accurate alignments independently of the portion of the resected tissue depicted in the intra-operative image (partial or complete tumor resection). On the contrary, the PBNRR cannot compensate for the large deformations induced by the resection and shows significant misalignments nearby the tumor cavities.

3.3. Performance evaluation

In this paper we perform all the experiments in a Dell Linux workstation with 12 Intel Xeon X5690@3.47GHz CPU cores and 96 GB of RAM. Figure 5 shows the total (end-to-end) APBNRR execution time, for all the case studies, with 1, 4, 8, and 12 hardware cores. Because of the various implemented multi-threaded modules, our method is able to register the clinical data in less than 1 minute (between 34.51 and 56.17 seconds), as shown with green in Figure 5. We should point out that the APBNRR does not scale linearly with the number of the cores. There is a significant speed boost from 1 to 4 cores, but limited improvement from 4 to 12 cores. The reason is mainly that APBNRR has not fully parallelized yet (Figure 1), so the maximum achieved speedup is always limited by Amdahl's law. After the parallelization of the sequential modules (Figure 1) and especially the computationally intensive FEM Solver [6], we expect to reduce the end-to-end execution time by 30-40% and achieve the alignments in less than 45 seconds.

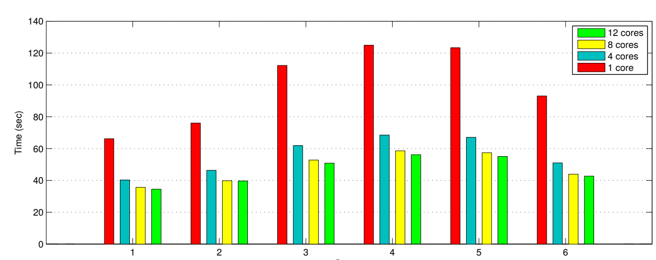


Figure 5. The APBNRR (end-to-end) execution time for the 6 clinical cases using 1, 4, 8, and 12 hardware cores.

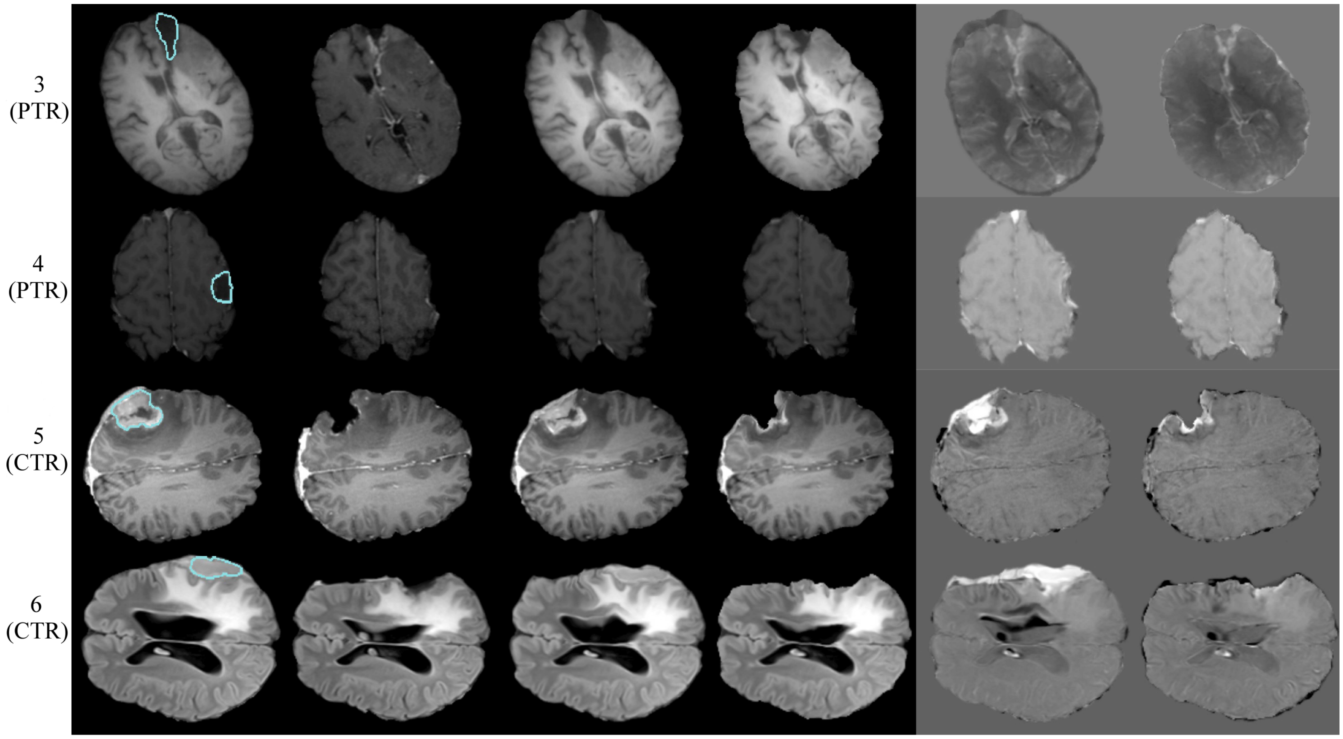


Figure 4. Qualitative evaluation results for the tumor resection cases. Each row represents a single case. The left margin indicates the number and the type of each case. From left to right column: pre-op MRI, intra-op MRI, warped pre-op MRI (PBNRR), warped pre-op MRI (APBNRR), warped pre-op MRI (PBNRR) subtracted from intra-op MRI, warped pre-op MRI (APBNRR) subtracted from intra-op MRI. For the PTR and CTR cases the cyan color delineates the tumor segmentation in the pre-op MRI.

4. SUMMARY AND CONCLUSION

We presented an Adaptive Physics-Based Non-Rigid Registration (APBNRR) framework to compensate for the brain deformations induced by a tumor resection.

The proposed method is built on the ITK open-source system and implements an adaptively changing heterogeneous (brain parenchyma, tumor), patient-specific, FE biomechanical model, to warp the pre-operative to the intra-operative MRI. We show that our framework can accurately handle the complex brain deformations associated with the neurosurgical procedure, independently of the portion (partial/complete) of the resected tissue depicted in the intra-operative MRI.

Our evaluation is based on clinical volume MRI data from 6 patients acquired from two hospitals. In all the conducted experiments our scheme exhibited high registration accuracy. It reduced the alignement error up to 6.61 and 4.95 times, compared to a rigid registration and the publicly available non-rigid registration method PBNRR of ITK, respectively.

Besides, most of the APBNRR modules are parallel. In all the case studies we tried in a Dell Linux workstation with 12 Intel Xeon X5690@3.47GHz CPU cores, our method needed between 34.51 and 56.17 seconds to register a pair of volume MRIs. Consequently, our scheme fits well within the time constraints (less than 1-2 minutes) imposed by the neurosurgery procedure. For this reason and considering the high accuracy of the provided alignments, we believe that our method has a potential use in the Operating-Room.

In the future, we will incorporate more tissues (e.g. brain ventricles) into the model in order to improve the registration accuracy. Also, we will parallelize the sequential modules to reduce further the end-to-end execution time.

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