Non–linear Registration of Pre– and Intraoperative Volume Data Based On Piecewise Linear Transformations

C. Rezk–Salama, P. Hastreiter, G. Greiner, T. Ertl

University of Erlangen, Computer Graphics Group
Am Weichselgarten 9, D–91058 Erlangen–Tennenlohe, Germany
Email: rezk@informatik.uni-erlangen.de

Abstract

For the planning of minimal invasive brain surgery detailed knowledge of the individual anatomical structures is necessary. Therefore in medical practice high–resolution MR image data is recorded preoperatively. Due to tissue resection and cerebrospinal fluid leakage both shape and position of the brain change during the intervention (brain–shift). Therefore intraoperative data is used in addition, providing exact anatomical information. In order to accommodate the deformations of tissue for computer assisted surgery, nonlinear registration of the voxel data must be performed. In this context we propose a new voxel–based approach based on maximization of mutual information. For fast evaluation the nonlinear deformation is modeled by adaptively subdividing the data set into piecewise linear patches. The parameters of this multi-dimensional transformation are optimized using Powell's direction set method. Since 3D–texture hardware is exploited to evaluate tri-linear interpolations, the registration process is significantly accelerated, which is of vital importance for the application in medical context.

1 Introduction

Computer assisted surgery aims at an improved instrument guidance based on tomographic image data. During surgical treatment of tumors or epilepsy, movement of the brain, tissue resection and leakage of cerebrospinal fluid lead to increasing discrepancies, that limit the use of preoperative data. Intraoperative MRI provides additional information to enhance orientation and resection control, being able to reveal significant tumor remnants. However, the image capability of intraoperative MRI is limited compared to conventional diagnostic MRI. For computer assisted analysis of the above mentioned tissue deformation (brain–shift), it is necessary to compare the preoperatively recorded image data to the actual situation during the intervention. Therefore a fusion of the two data sets is computed in order to analyze the nonlinear distortion.

Section 2 gives an overview of registration techniques for medical image data. The aim of all approaches is to adjust the free parameter of a selected transformation that maps one data set onto the other. Computation of the best fit according to a specified similarity metric results in an optimization problem of considerable complexity, depending on the chosen transformation type and the number of free parameters. With regard to the application in medical practice fast evaluation, stability and simplicity of the selected transformation is desirable. As described in section 3 the soft tissue deformation is modeled using piecewise linear patches. Section 4 comments on the optimization strategy used to maximize

mutual information. The following two sections describe acceleration techniques. Adaptive subdivision is used to minimize the overall number of free parameter for optimization as explained in section 5. Section 6 presents the application of 3D–texture mapping hardware for trilinear interpolation to accelerate histogram computation. Section 7 sums up the results of the presented approach and section 8 gives a brief outline of the contents of this paper.

2 Registration

Recent registration approaches are basically divided into three categories [3, 9, 8] according to the data features that are used as input for the alignment procedure.

1. landmark–based approaches use external fiducial markers or internal anatomical point landmarks to optimize a usually over-determined system of equations. These methods are mostly used to find rigid or affine transformations.

2. segmentation–based approaches use extracted anatomical features (points, lines, surfaces) inside the data, which are rigidly or elastically transformed for optimal alignment.

3. voxel–based approaches work directly on the voxel grey values. There is a variety of approaches using different similarity metrics for optimization. Since no pre-processing of the data is required, they are the most interesting methods of current research.

For accurate registration results, voxel–based similarity measures proved superior, since they are applicable to both mono– and multimodal data and no expensive pre–processing or segmentation is required. High accuracy is achieved by taking into account all the information that is inherent in the data. However, the use of voxel–based methods for volumetric data has yet been limited by the high computational cost.

3 Piecewise Linear Transformations

Transformations for registration of medical image data can be either linear (rigid, affine or projective) or non–linear. Although linear transformations are fast and simple to evaluate, due to their limited flexibility they are inadequate for modeling the complex deformation of soft tissue that is related to the brain–shift. Contrary to this, approaches using non–linear transformations are the methods of choice to accommodate tissue resection and deformation.

Non–linear registration was first introduced by Bajcsy et al. [1], who used an elastic deformable template model and a correlation–based similarity measure. Non–linear registration based on a viscous fluid model instead of elasticity was introduced by Christensen et al. [4]. This approach was significantly accelerated by Bro–Nielsen [2] using convolution with filter kernels. Thirion [12] proposed a similar method based on determination of force fields, that deform the image. Although these approaches are theoretically applicable to volumetric data, the computational effort for 3D registration is still immense.

With regard to clinical application, our aim was to find a transformation that is easy to evaluate with hardware acceleration. Furthermore, local optimization proved to be indispensable to apply for tissue resection such as excision of a tumorous region. Aiming at an efficient exploitation of graphics hardware, the idea was to use piecewise linear transformation of the floating data set to compute its 3D deformation for optimal alignment with the reference data set.

Throughout our experiments with piecewise curved transformations, software implementations of polynomial and Bezier tensor product patches turned out to be extremely time–consuming. On the other hand hardware implementations were restricted by the high complexity of polynomial patches and by limited hardware support for Bezier splines. In contrast to this we will show that fast and

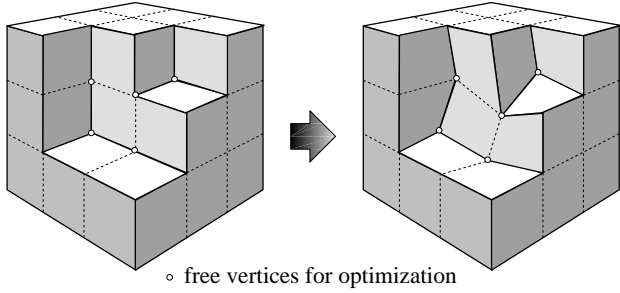efficient solutions are possible with piecewise linear transformation.

○ free vertices for optimization

Figure 1: Piecewise linear patches are used to model non–linear deformation of the volume data (some patches were removed to reveal the interior).

At first the floating data set is divided into an initially fixed number of linear patches as displayed in Fig. 1. For simplification we assume the positions of boundary vertices to be fixed. Subsequently, the transformation of every inner vertex is computed for optimal alignment with the reference data set using multi-dimensional optimization to maximize mutual information (see section 4).

To decrease the number of free parameter for optimization, adaptive subdivision is implemented in a straight–forward way as described in section 5. Since linear patches can be efficiently sliced into planar polygons, which are primitive objects for graphics hardware, the implementation can be significantly accelerated using the 3D–texture mapping capabilities of modern high–end graphics computers (see section 6).

4   Optimization

Selecting an appropriate optimization strategy in general comprises two major decisions. At first, an appropriate similarity metric must be chosen in order to evaluate the quality of a specific transformation. Furthermore, a numerical algorithm is needed to find an improved transformation if the quality of the previous one is unacceptable. According to this, the registration procedure consists of it-erative optimization and evaluation steps until the desired accuracy is achieved.

Mutual information was introduced as similarity metric for medical data by Collignon et al. [5] and Viola et al. [13] and proved superior to optimize rigid transformations of both mono– and multimodal registration [7]. Mutual information is a measure of relative entropy with its origin in information theory. Describing the statistical dependence of two random variables, mutual information is suitable to determine the amount of redundant information contained in both variables.

Let F be the floating data set represented by m samples $\{f_0, f_1, \ldots f_{m-1}\}$ with a marginal probability distribution $p_F(f)$. Analogously, the reference data set R consists of n samples $\{r_0, r_1, \ldots r_{n-1}\}$ with a marginal probability distribution $p_R(r)$. After applying the transformation T to the floating data set F, the joint probability distribution of R and F at corresponding locations x is denoted $p_{RF}(r(x), f(T(x)))$. For convenience, we will use r and $f(T)$ instead of $r(x)$ and $f(T(x)$ respectively.

In case that both data sets R and the transformed F are identical, their joint probability distribution satisfies

$$p_{RF}(r, f(T)) = p_R(r) = p_F(f(T)). \quad (1)$$

In contrast to this, if both signals are statistically independent, the joint probability distribution amounts to

$$p_{RF}(r, f(T)) = p_R(r) \cdot p_F(f(T)). \quad (2)$$

In the intermediate case the distances between the actual joint probability distribution $p_{RF}(r, f(T))$ and the ideal distribution $p_R(r) \cdot p_F(f(T))$ in case of independence are summed over all pairs of samples $(r, f(T))$. This results in the definition of mutual information

$$I = \sum_{(r, f(T))} p(r, f(T)) log\left(\frac{p(r, f(T))}{p(r)p(f(T))}\right). \quad (3)$$

Note that equation 3 reaches its maximum, if both signals R and F coincide. The optimal

transformation T_{opt} is thus denoted

$$T_{opt} = argmax[I(r, f(T))]. \qquad (4)$$

Since no assumptions are made about the two data sets, mutual information is not restricted to any specific modality and no pre–processing or feature extraction is required. The joint probability distribution $p_{RF}(r, f(T))$ can be graphically displayed as 2D compound histogram. Fig. 2 shows such a histogram in the case of multimodal data (CT and MR). The optimal transformation is found, if the dispersion of significant clusters in the histogram is minimized, which coincides with mutual information reaching its maximum.
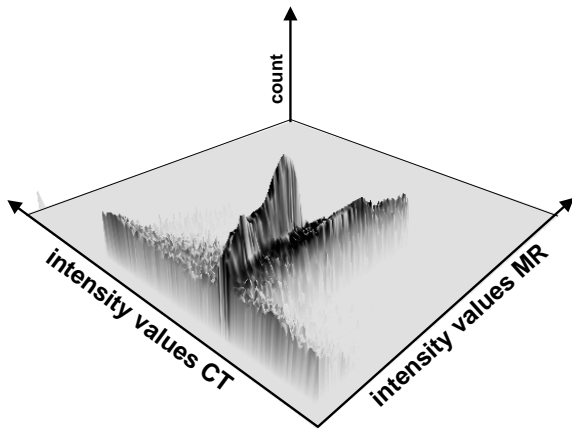

Figure 2: 2D compound histogram of multimodal data (CT and MR)

The second decision to be made is the selection of an appropriate numerical algorithm for multidimensional minimization. Direction set approaches are the methods of choice when explicit evaluation of derivatives should be avoided. Starting at an initial point in multidimensional space, the optimization process is split into a sequence of line minimizations. There are multiple strategies, that differ in the set of direction vectors they use. We chose Powell's original algorithm, which generates a set of mutually conjugate directions [11].

For registration of medical image data the computational effort for optimization is clearly dominated by the cost of evaluating

the transformation and the similarity measure. In this context acceleration techniques as described in the following sections are of great importance.

5   Adaptive Subdivision

In case of static subdivision the volume data set must be divided into a large number of piecewise linear patches in order to achieve registration results of high accuracy. To avoid the resulting huge amount of free vertices for optimization, a straight–forward approach is to use adaptive subdivision which generates a hierarchical structure of piecewise linear patches. Fig. 3 explains the 2D case of adaptive subdivision according to a specified refinement criterion. In the first step the optimal position of the inner vertices are computed. Subsequently the refinement criterion is evaluated for each optimized patch. We assume that the patterned regions in Fig. 3 are patches, that need to be further refined. Subdivision is then performed for the selected patches, introducing new free vertices. This procedure also results in new constrained vertices that are located at the boundary between patches with varying refinement levels. These are vertices, whose positions are not completely fixed but constrained to the position of neighboring free vertices. In the following optimization step new positions for all free vertices are computed and the locations of the constrained vertices are updated. This process is iteratively repeated several times until the desired accuracy is reached or no further improvement is achieved.
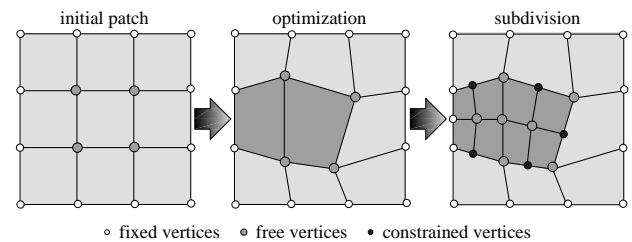

Figure 3: Adaptive subdivision generates a hierarchical structure of piecewise linear patches

To determine whether a selected patch should be further subdivided or not, an appropriate local refinement criterion is required. For mutual information an upper limit can be specified in terms of relative entropy

$$I_{RF} \leq min(H(R), H(F)) \qquad (5)$$

with $H(R)$ and $H(F)$ being the entropy of the random variables R and F, which amount to

$$H(R) = -\sum_a p_R(r) log p_R(r) \qquad (6)$$

and

$$H(F) = -\sum_a p_F(f) log p_F(f). \qquad (7)$$

For every linear patch g_i its contribution I_i to mutual information

$$I_i = \sum_{(r,f) \in g_i} p(r, f) log\left(\frac{p(r, f)}{p(r)p(f))}\right). \qquad (8)$$

and the upper limit

$$H_{min}(R_i, F_i) = min(H(R_i), H(F_i)) \qquad (9)$$

is computed respectively, which results in an appropriate criterion for refinement

$$0.0 \leq \frac{I_i(R, F)}{H_{min}(R_i, F_i)} \leq \vartheta \leq 1.0. \qquad (10)$$

The user–defined threshold value ϑ can be used to control the subdivision process and is heuristically set to $0.7 - 0.8$. Note that for very small patches, the evaluation of this refinement criterion becomes less accurate, due to the limited number of samples that are used. This problem can be solved in an efficient way by the use of hardware accelerated interpolation as described in the following section.

6   Hardware Acceleration

High–end graphics workstations allow the application of 3D–texture mapping with hardware accelerated trilinear interpolation. This hardware feature, which is usually exploited for interactive direct volume rendering, can be efficiently used to speed up the registration process.

At first, the floating data set is loaded into the 3D–texture memory. For each slice of the reference data set the corresponding deformed slice of the floating data set is reconstructed (see Fig. 4). This is achieved by linear interpolation between the free vertices of the transformation. This results in a deformed slice consisting of non–planar quadrangles, represented by the large grey dots in Fig. 4. Subsequently, the slice is explicitly triangulated (see below) and the resulting vertices are directly used as 3D–texture coordinates. The original untransformed polygon slice is then drawn into the frame buffer, textured with the corresponding grey value information directly obtained from 3D–texture memory by trilinear interpolation. The contents of the frame

○ vertices computed from transformation
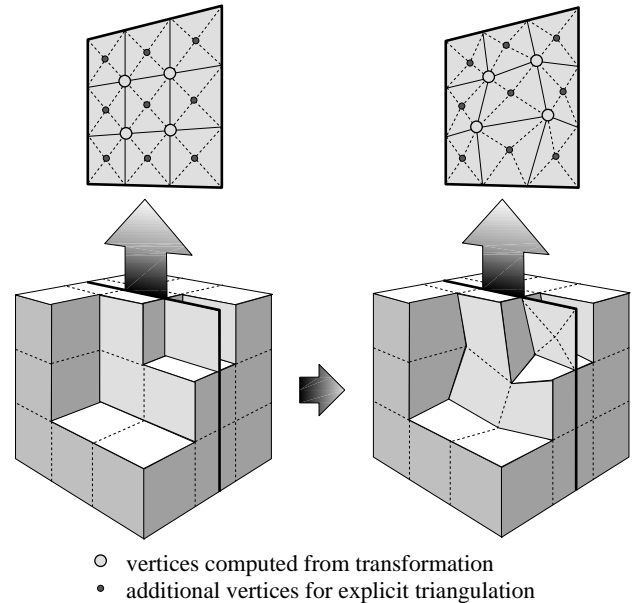• additional vertices for explicit triangulation

Figure 4: For hardware acceleration deformed slices of the volume are rendered

buffer is read out and the corresponding slice of the reference data set is then used to compute the 2D compound histogram which is required for mutual information. This procedure is repeated for all slices of the reference data set. Since hardware interpolation is used, the histogram evaluation is significantly accelerated compared to pure software solutions.

Explicit triangulation of the non–planar quadrangles is necessary on one hand to generate planar polygons. On the other hand additional vertices (the small black dots in Fig. 4) must be inserted to correctly render the non–linear deformation. Fig. 5 shows a non–planar quadrangle which results from movement of a single vertex *(a)*. Triangulation without inserting an additional vertex will result in an incorrect deformation *(b)*, since the patterned triangle remains unaffected by the vertex movement. Inserting an additional vertex *(c)*, whose position is an average of the four corner vertices, renders the correct deformation of the whole quadrangle.
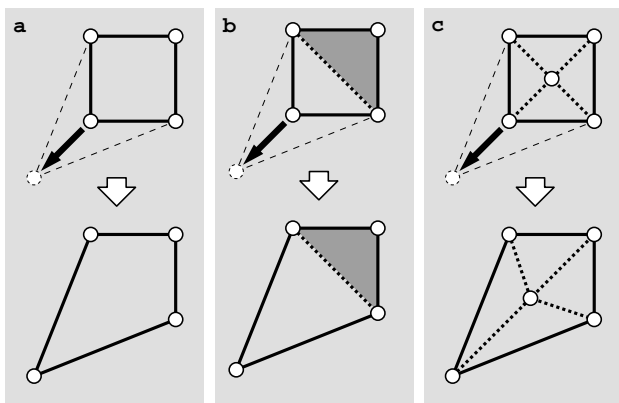

Figure 5: For explicit triangulation additional vertices have to be inserted to ensure correct deformation

To evaluate the refinement criterion as explained in section 5, the 2D histogram of a single patch must be computed. As mentioned above, accuracy is limited by the number of sample points used for evaluating mutual information. Using the texture mapping hardware this can be avoided by zooming the respective polygons to an appropriate viewport size, when drawing into the frame buffer. Thus an increased number of pixel will be used to compute mutual information with little loss in performance. This way, the size of the viewport can be used to trade accuracy for speed.

7   Results

The presented approach was evaluated for both 2D and 3D registration. Throughout our experiments we used pre– and intraoperative T1–weighted MRI data with a matrix of 256×256 and $80 – 128$ slices. The data sets were pre–registered rigidly using anatomical landmarks. The non–linear registration procedure was performed on a SGI Onyx2 (R10000, 195MHz) with BaseReality graphics hardware providing 64 MB of texture memory.
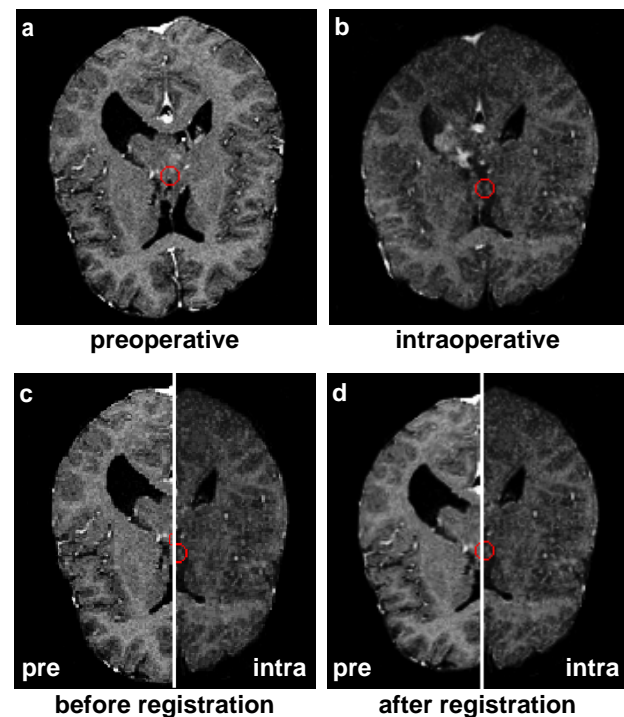
2D PIECEWISE LINEAR TRANSFORMATION

Figure 6: 2D registration of preoperative data (a) and intraoperative data (b). To accommodate the non–linear tissue deformation (c), piecewise linear transformation of the preoperative data set is performed (d)

For comparison, registration of 2D image data was computed with hardware acceleration as well as with a pure software implementation. Fig. 6 shows the results of 2D image registration with an initial 3×3 subdivision and a maximum refinement level of 2. Performance information for both procedures are displayed in table 1, which shows

that exploiting 3D–texture hardware is about two orders of magnitude faster than the pure software solution.

performance for 2D image registration software implementation

dimension in voxels	resolution in mm	registration time in sec
256×256	0.9×0.9	$1.1 \cdot 10^3$

performance for 2D image registration hardware implementation

dimension in voxels	resolution in mm	registration time in sec
256×256	0.9×0.9	22

Table 1: Performance of 2D registration

In case of 3D non–linear registration our method is able to model tissue deformation with high accuracy. The results in Fig. 7 were obtained using an initial subdivision into $3 \times 3 \times 3$ patches and a maximum refinement level of 3. The resulting data sets were visualized and validated using direct volume rendering. Fig. 8 shows the fusion of pre– and intraoperative data, which is examined using clipping planes.

performance for 3D registration hardware implementation

dimension in voxels	resolution in mm	registration time in sec
$256^2 \times 128$	$0.9^2 \times 1.3$	$1.34 \cdot 10^3$

Table 2: Performance of 3D registration

The results of performance measurement for 3D registration are displayed in table 2. Additional acceleration techniques of the presented approach, like fast histogram computation using the OpenGL histogram hardware extension [6], are topics of our future research.
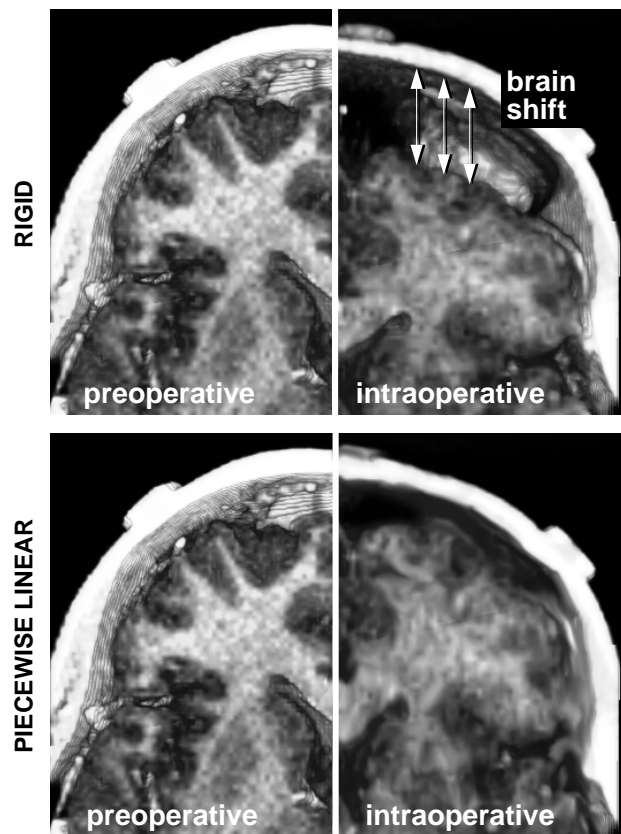

Figure 7: 3D registration: In order to analyse the brain–shift (top), non–linear deformation of intraoperative data is modelled using piecewise linear patches (bottom).

8 Conclusion

In this paper we proposed a new approach for non–linear voxel–based registration of multimodal medical volume data, aiming at high performance. Piecewise linear patches with adaptive subdivision are used to model the non–linear tissue deformation that is related to the brain–shift. The parameters of the multidimensional transformation are optimized using Powell's direction set method to maximize mutual information. Additionally the 3D–texture mapping hardware of modern high–end graphics workstations is efficiently exploited to significantly speed up the optimization procedure.
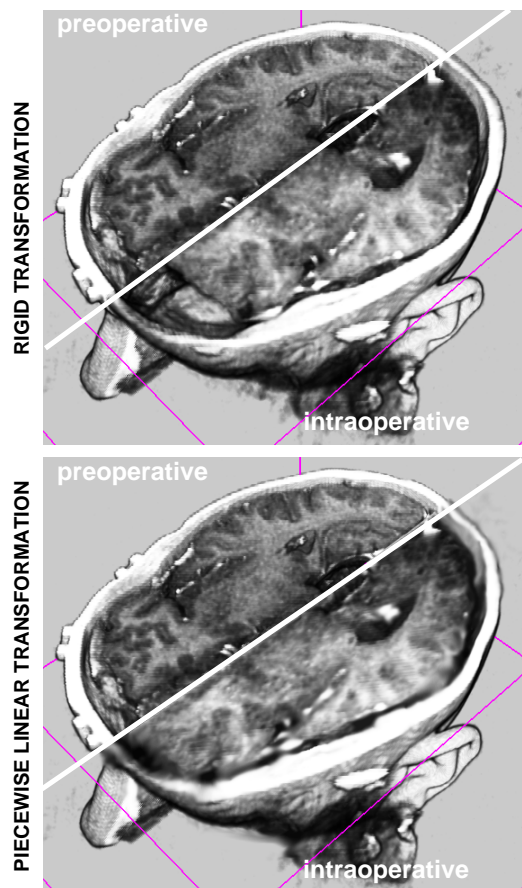
Figure 8: Direct volume rendering of pre– and intraoperative data after rigid registration (top) and piecewise linear transformation of the intraoperative dataset (bottom).

9 Acknowledgements

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