Preliminary Study Investigating Brain Shift Compensation using 3D CBCT Cerebral Vascular Images

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Abstract. During a neurosurgical procedure, the exposed brain undergoes an elastic deformation caused by numerous factors. This deformation, also known as brain shift, greatly affects the accuracy of neuronavigation systems. Non-rigid registration methods based on point matching algorithms are frequently used to compensate for intraoperative brain shift, especially when anatomical structures such as cerebral vascular tree are available. In this work, we introduce a pipeline to compensate for the volumetric brain deformation with Cone Beam CT (CBCT) image data. Point matching algorithms are combined with Spline-based transforms for this purpose. The initial result of different combination is evaluated with synthetical image data.

1 Introduction

Image guided navigation systems (IGNS) have become an essential part of neurosurgical procedures due to their ability to maximize the extent of tumor resection and minimize surgical trauma. However, the accuracy of image guided neurosurgery is greatly affected by the so-called brain shift phenomenon. This time dependent elastic deformation of brain tissue during surgery is not recovered by conventional navigation systems, as they typically assume rigid behavior of the head and its contents [1]. Without any intraoperative image update procedure, the anatomical information captured by preoperative MRI is no longer useful for surgical guidance as it does not account for the induced soft tissue deformation. Hence, updating the preoperative image data based on intraoperative images is a major challenge in image guided neurosurgery. Different intraoperative modalities such as MR, Ultrasound, Laser Range Image and Stereo Vision are used to update the preoprative image [2]. In this work, we introduce a new pipeline to compensate intraoperative brain shift by using 3D vascular tree captured with cone beam CT (CBCT). Generally, we use the bifurcations on the vascular tree geometries as anatomical landmarks to calculate a sparse displacement field, which is transformed to a dense displacement field reflecting the deformation between preoperative brain image and its intraoperative state. We implemented state-of-the-art point matching algorithms [3, 4] and spline-based transformations [5, 6] in the context of brain shift compensation.

2 Materials and methods

The overall brain shift compensation pipeline presented in this study includes the following steps: extraction of anatomical landmarks from the 3D vascular image, use point set registration to identify homologous points, and finally, interpolate the sparse displacement field on to a dense grid and updating the undeformed (preoperative) image using the estimated deformation field. The proposed method is evaluated using synthetic CBCT data. An elastic deformation is introduced to the prefrontal part of our digital phantom in the way described in [7]. Since the clinical data is not free of noise, the landmarks selected as described in section 2.1 contains outliers. Thus, we added 20% random outliers to the selected landmarks to evaluate the robustness of the methods.

2.1 Feature extraction

The bifurcation points on the vessel tree were segmented automatically with vesselness filter [8] and Otsu's method [9]. The centerline is extracted by using an octree data structure which examines the neighborhood of a pixel [10]. We use a 3x3x3 window centered at each voxel lying on the centerline to detect the bifurcation points. A bifurcation point is defined as the voxel which has more than two neighboring voxels on the centerline.

2.2 Point matching and spline based transformation

After the segmentation and feature extraction, the resulting two 3D point sets act as sparse anatomical landmarks on undeformed (pre-) and deformed (intraoperative) images. In order to find one-to-one correspondence between the two point sets and reduce the impact of noise and outliers, we investigated the Robust Point Matching (RPM) [3] and Coherent Point Drift (CPD) [4] for non-rigid registration. Robust Point Matching was formulated as a joint estimation of pose and correspondence using the softassign and deterministic annealing algorithm. The core idea is to optimize a fuzzy assignment least squares energy function which includes a smoothness term, an entropy term which controls the fuzziness and a regularization term that controls the proportion of points considered as outliers. In contrast to Iterative Closest Point (ICP) where the correspondence of two points is binary, softassign allows the correspondence of two points to be anywhere from zero to one. This enables fuzzy, partial matches between the source and target point sets. Coherent Point Drift was introduced as a probabilistic approach for both rigid and nonrigid point set registration. The authors consider the alignment of two point sets as a probability density estimation problem where

Table 1. Relative overlap rate of the complete brain tissue and region of interest (ROI) after using different point matching and interpolation techniques.

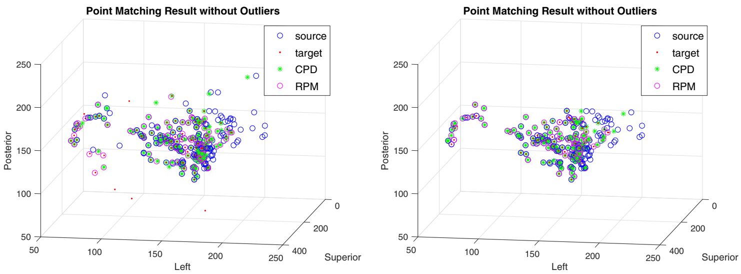
Scenario		Before	CPD-B	CPD-TPS	RPM-B	RPM-TPS
(1)	Full Brain	0.9178	0.9371	0.9376	*0.9532*	0.9272
(2)	ROI	0.8864	0.9316	0.9229	*0.9374*	0.9028
(3)	Full Brain (with outlier)	0.9178	0.8531	0.6622	0.8523	0.6494
(4)	ROI (with outlier)	0.8864	0.8793	0.8171	*0.9230*	0.8248

the source point set represents the GMM centroids and the target point set represents the data points [4]. Two point sets are registered by estimating a set of transformation and model parameters that maximize the posterior probability of target point set. In order to preserve the topology of the shape being registered, the GMM centroids are forced to move coherently. For the nonrigid point matching, a displacement regularization term based on the motion coherent theory [11] is incorporated into the cost function that is optimized (Matlab implementation available at https://sites.google.com/site/myronenko/research/cpd). Thin Plate Spline transformation [5] belongs to the family of Radial Basis Function and interpolates n-dimensional scattered data to continuous space. The concept of Thin Plate Splines is based on the theory of deformation of thin elastic plates, where the bending forces are orthogonal to the surface. For each control point (source point), the distance to all points on the homologous point set (target point set) is calculated. The weighted sum of the distances is used to formulate the TPS at each point, which implies a control point, which is far away from a certain point, still has influence on the position of this point. Another popular choice to interpolate the deformation between control points is to use B-spline. In context of medical image registration, this approach was first proposed in [6]. In order to estimate an accurate and smooth dense displacement field based on the control points, we used the multi-resolution approach provided in [6]. B-splines are locally controlled, which means the position of a certain control point only affects the transformation of the points in its neighborhood.

3 Results

Four approaches to brain shift compensation were investigated in this study: CPD with Bspline transformation (CPD-B), CPD with TPS transformation (CPD-TPS), RPM with Bspline transformation (RPM-B) and RPM with TPS transformation (RPM-TPS). The point set registration results for CPD and RPM are visualized by the plots shown in Fig. 1. For the quantitative evaluation, the brain tissue on the source, target and result images were segmented manually with 3D Slicer. The Relative Overlap Metric described in [12] was used as evaluation metric. We calculated it both for the complete brain tissue and the region where we introduced elastic deformation (ROI) to compare the global and local impact of TPS and Bspline tranformations.

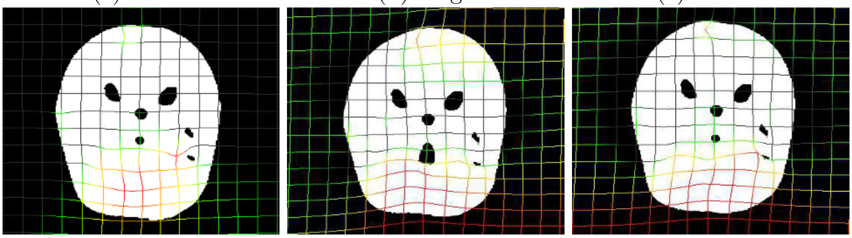
Fig. 1. Scatter plot of the point matching result for both data sets : (a) with 20% random outliers and (b) bifurcation points estimates as described in section 2.1. The hyperparameters for CPD was set as follows: $\beta = 0.2$, $\lambda = 10$, outlier weight $= 0.2$ in (a), $\beta = 0.2$, $\lambda = 10$, outlier weight $= 0$ in (b). For RPM, we used the default parameter setting suggested in the original paper.



(a) with outliers (b) without outliers

The relative overlapping rates are shown in Tab. 1. In the fourth scenario, only RPM-B is able to cover the deformation in ROI. However, for the data set containing outliers, there was no improvement in the overlap metric for the entire brain region (relative to the baseline). With the exception of the third scenario, where the combination of CPD and B-spline transformation achieved a slightly better result than the combination of RPM and B-spline transformation, RPM-B always outperforms the other three methods. Although the highest overlapping rate is calculated in the first scenario, the most improvement can be observed in the second scenario.

(c) source (d) target (e) CPD-B



(f) RPM-B (g) CPD-TPS (h) RPM-TPS

Fig. 2. An example axial slice with displacement field overlay. (a) and (b) are the source and target images. (c) - (f) are registration result of different methods.

4 Discussion

In this work, we introduced a new pipeline for brain shift compensation with intraoperative image data from CBCT. State-of-the-art point matching methods and spline based transformation techniques are employed for this purpose. Initial result on synthetic image data shows RPM combined with B-spline transformation is basically a good choice. It is the most robust combination against outliers and keeps the deformation localized. Table 1 shows, outliers affect the accuracy of the methods greatly, especially for TPS based methods in our experiments. A common practice to improve the performance of TPS transformation is to insert extra landmarks manually where no deformation is expected to occur. Overall, the TPS based methods are less accurate than their B-spline counterparts. Compared with baseline, both CPD-TPS and RPM-TPS achieved better results in the two cases where outliers are absent. With the introduction of outliers, the results are reversed. This behavior is consistent with the theory of TPS: it is a globally controlled transformation and sensitive to the choice of control points. This characteristic can be also observed in Fig. 3. B-spline transformation affects changes only in the neighborhood while TPS introduces deformation to the entire image volume. The result in Fig. 1 shows, RPM behave more robust against outliers but CPD is able to find the right correspondence for the points where RPM could not find correspondence. This is based on the different outlier handling strategies: RPM is rejecting outliers per se with a regularization to avoid too much rejections. CPD includes a hyperparameter which controls the relative importance of outliers compared to the Gaussian components in the mixture model. Another qualitative finding obtained from Fig. 3 is, that in comparison with RPM based methods, CPD tend to introduce more undesirable deformation to the subsurface structure (e.g. ventricle). This observation will be further investigated and quantified in furture work. Since there is, rarely if ever a Gold Standard to evaluate image registration results, no metric alone is sufficient to evaluate the performance of a nonrigid registration method [12]. Hence, other evaluation metrics such as target registration error should also be considered in the further experiments. A possible approach is to calculate the ground truth deformation of the volumetric meshes by comparing the deformed and non-deformed meshes at first, then interpolate this vector field into the image volume. Based on this ground truth deformation field, the exact difference between the displacement calculated with our proposed pipeline and actual displacement at each voxel can be obtained. Another important aspect of intraoperative brain shift compensation is the computational expense and numerical stability of the algorithm. B-splines are locally controlled, which makes them computationally efficient even for a large number of control points. In contrast, TPS transformation is computational expensive for large number of control points, since it considers every control point for each voxel. Our experience also shows the calculation of the inverse of L Matrix (see original paper [5]) is very crucial for the accuracy and numerical stability of TPS transformation. Since the L Matrix is often not invertable, numerical tricks such as pseudo inverse or Tikonov regularization are used to solve this problem. This is at the expense of the accuracy of the calculation result. In context of TPS transformation, a minimal error of each value in the inverse L Matrix leads to a summation of the error which produces implausible deformations. Due to these reasons, we propose to use B-spline transformation instead of TPS in subsequent studies.

Disclaimer. The concepts and information presented in this paper are based on research and are not commercially available.

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