Segmentation-Enhanced Registration of Angiography Data

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Abstract. For diagnostic and therapeutic purposes, multiple imaging techniques can be used to gain more information on a patient's anatomy. In maxillofacial and neurosurgery, three-dimensional rotational angiography (3DRA) images can provide a detailed view on blood vessels, whereas computed tomography angiography (CTA) images are common for multiplanar interpretation of bone, soft tissue, and blood vessels. Thus, the registration of 3DRA to CTA allows for a better understanding of the structure and location of blood vessels within a context of bone and tissue, which is essential to surgical interventions. Among other reasons, the lack of mutual information between 3DRA and CTA images makes their registration challenging. In this work, we describe an approach that is based on a segmentation of common structures of the datasets, which enhances the mutual information and hence, the registration result. An evaluation and a comparison to the registration accuracy of unsegmented datasets is presented.

1 Introduction

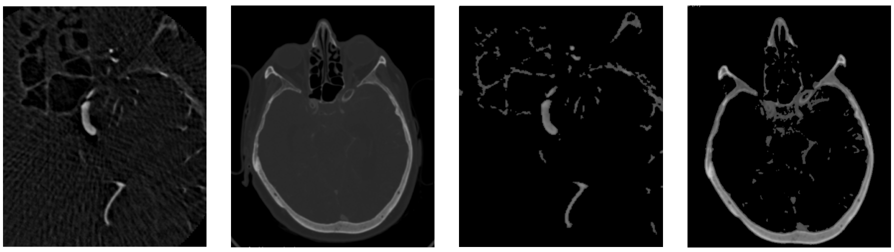
Three-dimensional rotational angiography (3DRA) provides detailed 3D information, needed to examine a patient's vasculature from arbitrary view points and to get an understanding of its individual shape. To acquire additional information about surrounding bone and soft tissue, which is essential for surgical intervention planning, further imaging techniques, such as CT angiography (CTA), are used. Here, however, the imaged vasculature is less detailed and these modalities do not allow for an easy phase control (i.e. imaging of only arteries or veins). Accordingly, for the surgeon, a combined exploration of 3DRA and CTA data enables detailed information on blood vessels (from 3DRA) in the context of bone and tissues (from CTA). Here, we focus on the registration of 3DRA to CTA data of the head, which is not straight-forward, due to the different spatial resolutions of the datasets, the fact that the datasets are often taken from different viewing angles, and especially the lack of mutual information in these modalities (Fig. 1 a,b). Therefore, we enhance their mutual information by segmenting structures represented in both datasets (i.e., vessels) and achieve a more accurate registration result when using these segmented gray value images as input.

2 Material and Methods

Mutual Information (MI) methods are considered standard for multimodal rigid registration problems [1] and we therefore based our approach on the MI algorithm introduced in [2]. However, there is little mutual information between 3DRA and CTA [3], which renders MI registration difficult. We enhance the mutual information by segmenting the shared anatomical structures of the two datasets. In this case, the major vessels and bone structures constitute overlap information, because of angiography information in the CTA image and some (low-contrast) representation of bone in 3DRA. In contrast, the inhomogeneous background structures of 3DRA – providing only a low signal-to-noise ratio [4] – decrease the quality of registration results (Fig. 1 a). Preprocessing of the 3DRA dataset is implemented using a median filter at first – to reduce noise while preserving edges – and afterwards apply a region-growing to select bone and vessel structures (Fig. 1 c). For the CTA data, a vesselness filter [5] is used to extract blood vessel information. The final segmentation of vessels and bone is also performed with region-growing (Fig. 1 d). For the selection of the seed points user interaction is required. The thresholds for the other segmentation methods, such as region-growing or vesselness filtering are pre-defined, but can be adjusted by the user if needed.

Our method also allows for an optional initialization step. Here, the spatial correspondence between user-defined landmarks is calculated by minimizing a least-squares distance cost function. Since it is inherently difficult to choose landmarks in two datasets collected at different spatial resolutions and from different viewing angles [6], the segmentation step simplifies the choice of identical landmarks.

A modified version of the *full circle consistency test* as described in [3] is used to determine a quality index e (in millimeter), representing the method's accuracy. Three registrations are performed between three datasets (Fig. 2): 3DRA dataset, original CTA dataset (CTA1), and a dataset (CTA2) obtained by rotating CTA1 by 10° around the X axis and translating it 5 mm in each



(a) (b) (c) (d)

Fig. 1. The modalities 3DRA (a) and CTA (b) differ concerning resolution, field of view and mutual structures. On the right, the respective segmentations of 3DRA (c) and CTA (d) are shown as they are used as registration input.

direction. We let M_{3DRA}^{CTA1} be the transformation of 3DRA dataset to the CTA1 dataset (M_{CTA1}^{CTA2} and M_{CTA2}^{3DRA} named analogously).
For a perfectly accurate registration without any errors, the following will hold:

$$M_{CTA2}^{3DRA} * M_{CTA1}^{CTA2} * M_{3DRA}^{CTA1} = I \quad (1)$$

where I is the identity matrix. If there are any errors, the accumulative error will be equal to

$$E = I - M_{CTA2}^{3DRA} * M_{CTA1}^{CTA2} * M_{3DRA}^{CTA1} \quad (2)$$

From this matrix E, the rotational and translational errors can be extracted. For a better comparability, these errors are transferred into the quality index e converting six error values into a single measure (for details, see [3]). A quality index below 2 mm corresponds to a satisfying registration result, whereas a quality index below the datasets' maximal voxel size is considered excellent.

Four pairs of patient datasets (3DRA and CTA) were available to perform the preprocessing and the described accuracy measurement. With that, the segmentation-enhanced registration was evaluated and compared to the results of the same registration applied to the original (i.e. unsegmented) datasets.

3 Results

After preprocessing, the 3D landmark initialization step is used for a preliminary registration. As this step is based solely on finding the optimal transformation between user-chosen landmarks, it performs as well as the integrity of the chosen landmarks. As can be seen in Figure 3a, the initial registration aligns the images reasonably well, but there is still significant mismatch. The subsequent MI registration finds the optimal transformation. A preliminary visual inspection of the resulting overlay shows a very good registration result (Fig. 3 b) promising a high accuracy. Table 1 shows the difference in accuracy of the segmentation-enhanced registration and the registration of the original datasets. In each case, identical landmarks were used for the segmented and original datasets to allow a precise comparison of the results. With a quality index e below or equal to

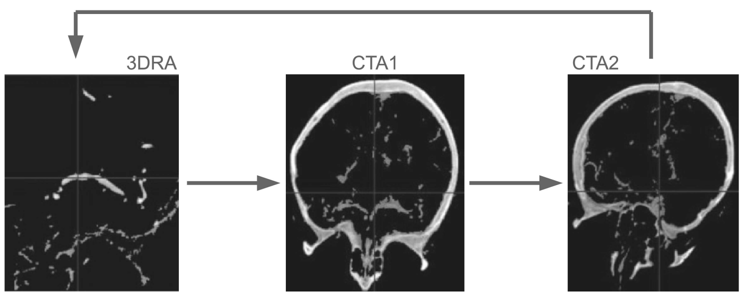


Fig. 2. Registration circle used for evaluation.

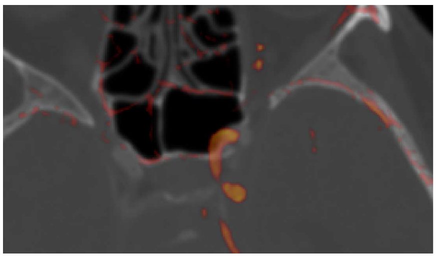
Table 1. Registration accuracy in four cases for segmentation-enhanced registration (second column) and the original method (third column). The right-most column depicts the maximal voxel length of the registered datasets.

Case	Quality Index e [mm]		Maximal Voxel Size [mm]
	original	segmented	
1	0.53	0.36	0.7
2	0.92	0.51	0.7
3	1.87	1.29	0.53
4	2.02	0.87	0.53

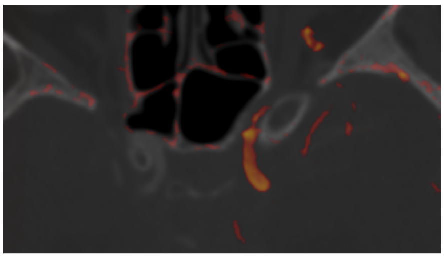
2 mm, the registration accuracy is satisfying for the original datasets (Section 2). In case 1, a very good result of 0.53 mm, which is below the maximal voxel size of 0.7 mm (right-most column) is achieved. Compared to this, segmenting the mutual structures of the datasets increased the accuracy by at least 32 %, in case 4 even by 56 %.

4 Discussion

The registration of 3DRA to CTA allows the visualization of vascular details within a context of bone and soft tissue, giving a better understanding of the structure and location of blood vessels. Such a registration is essential for the planning of surgical procedures [7] and has to be fast and highly accurate to meet the needs of the clinical use. Due to the many challenges of registering 3DRA to CTA, an automatic registration can be difficult. In this paper, we presented a successful semi-automatic framework for the registration of volumetric angiography datasets using segmentation and a landmark initialized MI rigid registration algorithm. We showed that enhancing the mutual information by



(a) Initialization result



(b) Registration result

Fig. 3. The landmark initialization step registers the images according to the user-defined landmarks (a). The MI registration refines the registration based on the gray value information of the segmented images (b). (Shown for Case 1; segmented 3DRA data over CTA dataset).

segmenting the datasets' common structures improves registration accuracy. A convenient side-effect is that the segmentation may simplify landmark selection.

Although the preprocessing results in a time overhead compared to using the original datasets directly, the findings are promising. More evaluations concerning the robustness of the method, the influence of the segmentation exactness as well as the number and position of landmarks on the registration results are planned. Furthermore, this approach is not limited to head datasets or CTA data. Thus, an application to heart datasets as well as magnetic resonance angiography data is planned for the near future. Still, further work is needed to reduce the segmentation overhead in order to make this approach competible to faster methods in the clinical application. For this, we aim at a more automatic segmentation and an automization of the landmark initialization. In contrast to the quite invasive stereotactic frame registration of [8], we envision a process based on the automatic detection and identification of fiducial markers.

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