ROBUSTNESS OF MUTUAL INFORMATION BASED INTRA-OPERATIVE REGISTRATION

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Abstract

We investigated the robustness of the registration of intra-operative 3D rotational angiography (3DRA) data with pre-operative anatomical data, such as CT and MR. The analysis has been done in the context of interventional treatment of vascular pathologies and endovascular treatment of the neoplastic tissue. We used Mutual Information as similarity measure, and the Powell algorithm as optimizer. The robustness was measured as function of translation in different directions and rotation around different axes, for 11 patients.

1 Introduction

3D rotational angiography (3DRA) has significantly improved standard 2D angiography imaging by making three-dimensional imaging directly accessible in the OR, during the intervention. As such, it enables a better understanding of the mutual relationship of vessel pathology and surrounding branches in minimally invasive neuro- and abdominal applications. In order to add the contextual information of the soft-tissue to the 3DRA images, we developed a method for registration with pre-operative CT or MR images, which may have been acquired earlier for diagnostic purposes.

Using 3D image registration during interventional treatment poses a number of constrains on the registration algorithm. Especially, the calculation time of the algorithm has to be limited, since the result of the registration is to be used during the intervention [1]. Typically a registration algorithm consists of a multi-dimensional similarity measure, indicating the quality of a given spatial mapping, and an optimization algorithm, which searches the optimum (maximum or minimum, depending on the measure) of the similarity measure. The search space consists of the control variables of the similarity measure, which are in our case translation in the x-, y- and z- direction, and rotation around the x-, y- and z-axis (rigid registration).

We used Mutual Information as similarity measure, as described by Maes et al. [2], because it performs very well on inter-modality registration, and does not need any a-priori knowledge of the datasets [3]. In order to limit the calculation time, we employed the Powell algorithm [4] as optimizer, which is a so-called local optimizer. Local optimizers are generally faster than global optimizers, but they do not guarantee that the overall optimum is found.

Our method is based on a rough manual pre-registration, to be performed by the clinician, followed by a finer automatic registration. To validate the applicability of our registration approach in the clinical practice, we investigated the robustness of the automatic algorithm, using clinical data. In this context we defined robustness as the extent of the parameter search space that can serve as start position for the optimizer, and still evolves to a correct spatial transformation between the datasets. If this robust extent is too small, the manual pre-registration becomes too cumbersome and time-consuming to be performed during an intervention.

2 Method

First we determined a golden standard transformation for every dataset pair. This was done by manually defining a starting position that was sufficiently close to the correct transformation, and then let the registration algorithm run. The results were then visually inspected, to assure that the transformation was indeed correct. All golden standard transformations were of sub-voxel accuracy.

To establish the range of the search space, where the algorithm behaves robustly, we made the following assumption: if a registration process, started from a translation in a certain direction, evolves to the golden standard transformation, each registration attempt from a smaller translation in the same direction is also assumed to lead to the golden standard transformation. Whereby we considered two transformations to be the same, if all the components of the rotation matrix differ less than a particular d_R (we used $d_R = 0.05$), and the translation differs less than d_T (we used $d_T = 0.5$ mm).

Based on this assumption, the robust translation extent was determined, using an approach, similar to a binary search [5]; The golden standard transformation was applied to the datasets, and one dataset was translated in a certain direction. If performing the registration process indeed lead to the golden standard transformation, the process was repeated with the translation vector doubled. If not, the translation vector was halved. This process was continued until a bounding interval (b_1, b_2), with $b_1 < b_2$, was found, whereby a translation of b_1 still was within the robust extent, and b_2 not. Then, iteratively a new limit $b = (b_1 + b_2) / 2$ was tested. If a registration started from a translation with vector b evolved to the golden standard transformation, b was within the robust range, and b_1 was set to b for the next iteration. Otherwise b_2 was set to b. In this way the accuracy of the boundary of the robust range was doubled (the uncertainty was halved) in every iteration.

The iterative process was continued until the boundary of the robust extent was found with an accuracy of 5 mm. Using this method, the robust translation range was determined for every patient in 14 distinct directions (see figure 1).

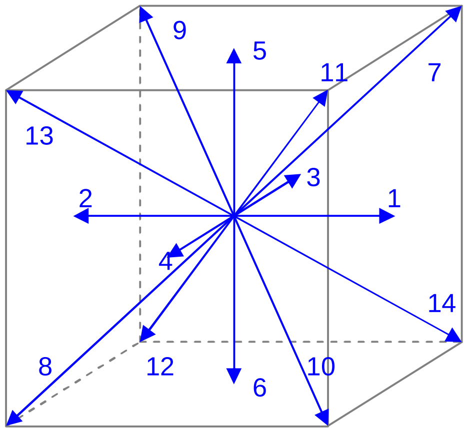

Figure 1: The translation of the datasets was tested in all 14 depicted directions.

A similar scheme was used to determine the robust rotation extent around the x-, y- and z-axes in both directions. The robust rotation range was determined with an accuracy of 1°.

The maximal initial translation and the maximal initial rotation were determined for dataset pairs obtained from 11 patients.

Figure 2: A slice out of a 3DRA dataset, showing the sinuses, the skull, and a contrast medium filled aneurysm

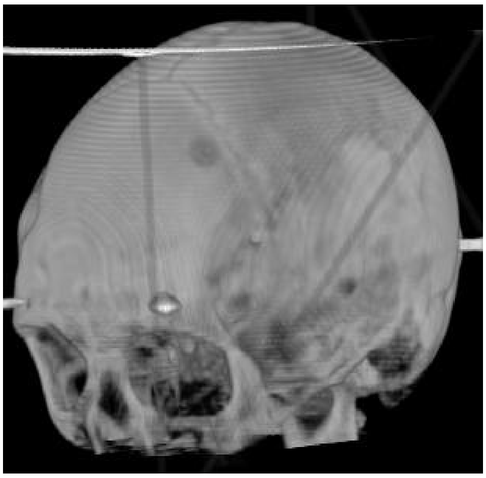

Figure 3: A CT dataset, containing the facial structures.

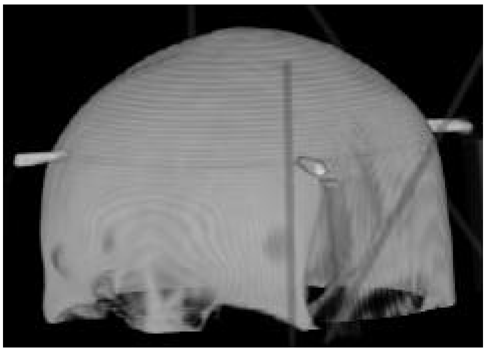

Figure 4: A CT dataset, missing a major part of the facial structures, which hinders the registration process.

3 Datasets

In spite of its very high spatial resolution (up to 0.1 mm), the 3DRA technique has a limited contrast resolution, and the resulting images are rather noisy. As a consequence, the voxels can be classified in only four categories: air, water (or materials with roughly the same x-ray absorption), bone, and contrast medium (see figure 2). The latter two categories can be distinguished clearly from air and water, since they absorb a considerably larger amount of the x-ray radiation. Noise is especially present in air and water (soft-tissue). Because of the limited contrast resolution, the registration process is primarily determined by the facial structures, such as the eye sockets, the nose, the sinuses, etc. It is therefore of importance that such structures are contained in both datasets (compare figures 3 and 4).

To enable a successful registration process, the CT or MR dataset should have enough spatial resolution in the slice direction. As a rule of thumb, we advice that distance between the slices should be no more than twice the pixel size.

4 Results

We tested the translation and rotation range that still could be registered robustly for 7 patients with a 3DRA - CT dataset pair, and 4 patients with a 3DRA - MR pair.

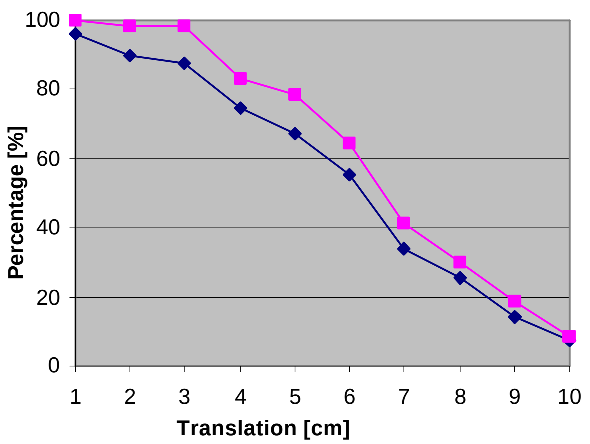

Figure 5: The percentage of 3DRA – CT dataset pairs that can be registered correctly, for a given initial translation. The upper line shows the results if the two most difficult to register patients are not taken into account. The lower line indicates the results for all patients.

The results with regard to the robust translation range are shown in figure 5. 88% of the CT datasets can be registered correctly when the registration process is started within 30 mm translation to the golden standard transformation with the 3DRA dataset. 67% manage to robustly register within 50 mm translation. The results we obtained are comparable, or slightly better than published by Stancanello et al. [6].

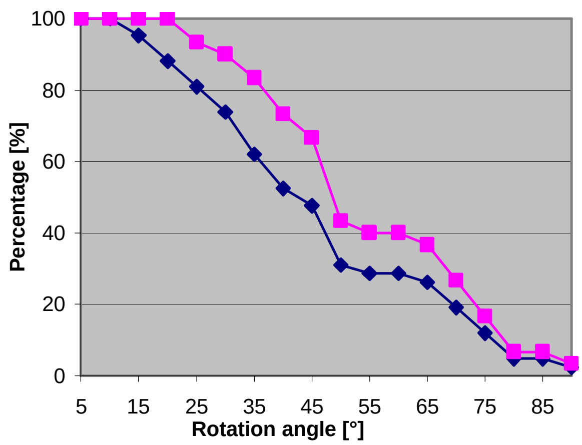

Figure 6: The percentage of 3DRA – CT dataset pairs that can be registered correctly, for a given initial rotation. Upper line: without the two most difficult to register patients. Lower line: the results for all patients.

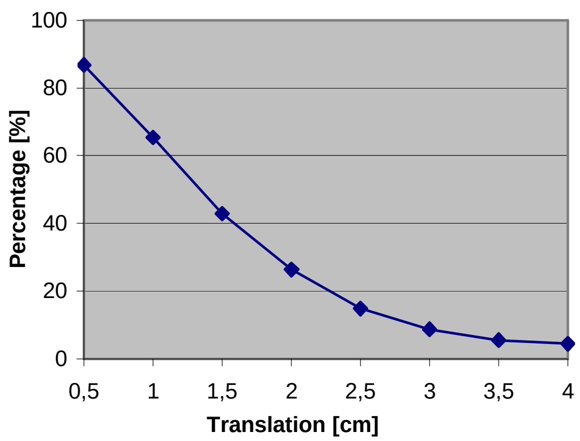

Figure 7: The percentage of 3DRA – MR dataset pairs that can be registered correctly, for a given initial translation.

The results of starting the registration process with the datasets rotated to each other, is illustrated in Figure 6. 88% still of the CT datasets can be registered correctly to the 3DRA dataset when the rotation is 20°, 74% when the rotation is 30°.

The results for the MR – 3DRA dataset pairs are shown in figure 7. Unfortunately not all MR datasets fulfilled the criteria that were described in section 3 (not enough landmark regions present, slices too far apart). However, more than 60% of the registration attempts still succeed when the translation is 10 mm.

5 Conclusions

The registration of intra-operative 3DRA datasets and pre-operative CT or MR datasets has great clinical relevance, since it adds contextual information to the intra-operative status of the vessel tree and endovascular devices. We have proposed a registration method and investigated its robustness, with respect to the initial translation and rotation of the datasets. We used a Mutual-Information driven registration algorithm, with the Powell method as optimizer. The maximal initial translation was searched in 14 distinct directions, and the maximal initial rotation around 6 rotation axes, for dataset pairs obtained from 11 patients.

The fact that 3DRA datasets are rather noisy and have a limited contrast resolution, limits the range where the registration robustly evolves to the correct transformation. However, still 88% of the CT datasets can be registered correctly with their 3DRA counterpart, when the registration process is started within 30 mm translation to the golden standard transformation and when the rotation is within 20°.

This can be easily achieved by pre-registering the datasets manually, and therefore this method is considered to be suitable for application during minimally invasive interventions.

References

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