Registration of CT and MRI volume data of the liver

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Abstract

The paper introduces a way to improve treatment planning of single–dose radiation therapy of liver tumors. Therefore a new algorithm for the registration of diagnostic MRI images and the computed tomography data used for treatment planning was developed. The described algorithm is divided into two stages. At first the two dataset are aligned by optimization of mutual information using rigid transformations. After this initial registration step a non–rigid transformation based on thin–plate splines is performed, modelling the deformations of the soft tissue. An algorithm for automatic control point computation was developed, which is supposed to simplify the time consuming task of defining the control points necessary for a thin-plate spline interpolation. The obtained results show that the implemented algorithm can successfully solve the registration problem.

Key words: non–rigid registration, multimodality, liver, radiotherapy planning

1 Introduction

Stereotactic single–dose radiation therapy is a promising way for the treatment of patients with liver metastases. A phase I/II trial showed good first results

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[1]. During treatment planning the target volumes and radiation doses are defined under the control of computed tomography (CT) data. During the treatment planning, the whole abdomen is compressed to minimize motion of the liver due to respiratory or digestive processes. This abdominal compression is necessary for a reproducible determination of the tumor position. A negative consequence of this compression is the very large deformation of the liver.

In the CT data, the liver metastases are often shown incompletely and sometimes one cannot see the tumor at all. Because of the good contrast of soft tissue in magnetic resonance images (MRI), the tumorous tissue can much better be identified and the volume definition is more exact in the MRI than in CT images. During treatment planning no MRI can be aquired, because the radio therapy equipment is not MRI compatible. For this reason a diagnostic MRI is recorded before treatment planning.

To support the physician during therapy planning, the information about the volume and position of the tumor has to be accessible for treatment planning. Therefore a registration of the MRI with the CT treatment planning data needs to be performed.

This work investigates the feasibility of such a data fusion, the registration of the MRI and the CT data, is possible. It is a problem of matching 3–dimensional multimodal image data of soft tissue. There are many known registration approaches which solve similar tasks, like matching PET and CT data or matching of CT sequences [2], but to our knowledge no work deals with non–rigid registration of 3D CT and MRI data of the liver. Furthermore the abdominal compression described above complicates the task in a high degree.

2 Methods

The implemented algorithm registers the MRI model volume data with the CT reference volume data in two steps. During the first step, an initial alignment of the images is obtained by application of rigid transformations. Because the liver consists of soft tissue, a rigid registration cannot model the liver's motions and deformations. The rigid registration is supposed to give the user a good starting point for the necessary computation of the non–rigid tissue deformations. The result of this first registration phase is then used as a starting point for the second registration step, which is based on non–rigid transformations to model the local deformations of the liver tissue. Before the registration of the data, a preprocessing step needs to be performed. The images are resampled in a preprocessing step, which is necessary to adapt the spatial resolution of the MRI and CT volume.

2.1 Registration Algorithm

During the first registration step, a rigid transformation is automatically optimized by maximization of normalized mutual information (NMI) [3]. NMI has proven as a good similarity measure for multimodality medical image alignment.

The non–rigid deformations were modelled with 3D thin–plate splines, which have shown good results in many non–rigid registration problems [4]. Furthermore the local deformations are easily controlled by defining control point pairs.

The control points necessary for the spline interpolation were defined in two different ways. In a first trial the set of control points was defined manually, which is a time consuming task and demands good anatomical knowledge of the liver. Therefore an algorithm was developed which automatically detects pairs of control points.

2.2 Hierarchical control point computation

Following the hierarchical approach to register 2D images presented by Likar et al. [5] we developed an algorithm for automatic control point computation for three-dimensional images.

At start of the algorithms the two volumes — the reference and the model image — are divided into eight cubic sub-volumes each (see fig. 1). Then each sub-volume of the model image is registered rigidly with the corresponding sub-volume of the reference. For each pair of sub-volumes one obtains a pair of center points. These are then used as the control points for the computation of the thin-plate spline interpolation of the model volume.

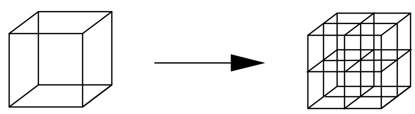

Fig. 1. Scheme of hierarchical division for subvolume registration

After applying the thin-plate spline transformation to the model image each sub-volume from step one is divided into sub-volumes again and the algorithm is performed iteratively.

The algorithm was validated on a phantom data set. Figure 2 shows the results of the experiment.

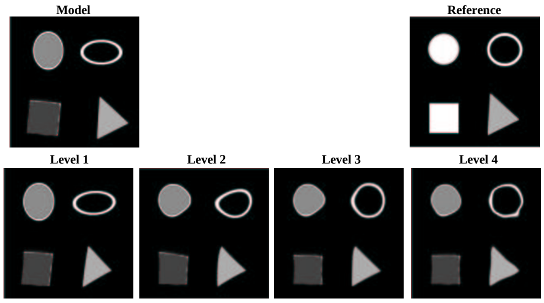

Fig. 2. Phantom slices registerd with thin-plate splines using hierarchical control point computation.(top: original data, bottom: results of the first four iterations)

The model image on the top left is transformed iteratively and the local deformations from the reference image (top right) are approximated correctly over the four levels as shown on the bottom line in figure 2. The results from the experiment show the algorithm's ability to model local non–rigid deformations.

3 Results

The implemented algorithm was tested with two different data sets, each consisting of a CT volume and an MRI volume. To measure the quality of the results, so-called landmarks (anatomic identical points) were defined in both volumes. For instance the center of a tumor or a vessel bifurcation in the liver, which are visible in MRI and CT as well, can be such landmarks. The defined landmark sets were transformed during the different registration phases. After each registration step, the mean square error of all landmark pairs was computed and analyzed.

After the preprocessing step, the volumes were automatically registered rigidly by maximization of mutual information. The results of automatic registration have shown that one achieves the same accuracy as if aligning the two data sets interactively. Using the transformed MRI model volume from registration step one and the CT reference volume, the thin-plate spline transformation was computed.

Several experiments using manually and automatically defined control points were performed. At first a registration with manually defined control points was computed. Figure 3 shows the overlay of corresponding slices before and after the non–rigid registration. The boxes mark the region where the local deformations of the CT were adapted.

The used landmarks were defined on the liver only, which caused the large deformations in the right half of the images.

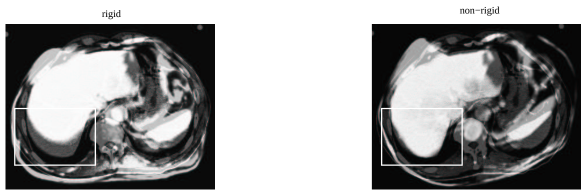

Fig. 3. Slice overlay of dataset 1 before and after non–rigid registration based on manually defined control points

Figure 4 shows a slice from an MRI image transformed with a thin–plate spline interpolation using automatically computed control points and the corresponding CT reference slice. One can see that the deformations of the liver are not retrieved correctly.

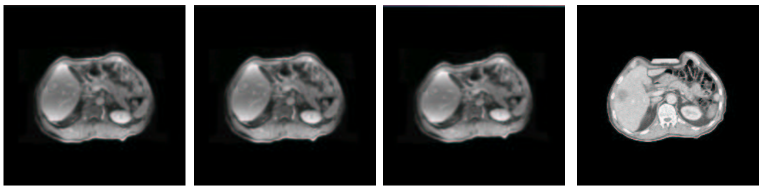

Fig. 4. Slices of dataset 1 non–rigidly registered based on automatic control point computation

The results achieved with manual control point definition are very promising. The mean square error (mse) of the defined landmark set decreased evidently for both data sets (see first line of tab.1). When applying the automatic control point computation algorithm the mse decreased in the first iteration of the algorithm, but immediately increased again in the next iterations for both data sets (see also tab.1).

	dataset 1	dataset 2
registration step	MSE [mm]	
after rigid registration	16,4	15,0
manual	8,8	11,2
automatic L1	14,3	14,9
automatic L2	16,3	14,5
automatic L3	17,9	16,8

Table 1
Mean square error of validation landmarks after thin-plate spline interpolation with manually and automatically computed control points.

4 Conclusion

The trial to implement a widely automatic registration algorithm was successful. The initial rigid registration phase creates the starting point for the non-rigid deformation of the model volume. The results of the second registration step show that very strong deformations of the reference volume caused by the abdominal compression can be modelled with the thin-plate spline interpolation used. It shows one possibility how the MRI data can successfully be registered with the CT data used for radiation therapy planning and how the good knowledge from the MRI about the size and position of the tumor can be made available for treatment planning. The results of the hierarchical algorithm for control point computation did not meet our expectations. A reason is the low statistical significance of the histograms for small sub-volumes.

It remains to be validated in how far the tissue deformations modelled with thin-plate splines correspond to the actual deformations of the liver caused by the abdominal compression. As a next step a trial should be performed, to validate the presented algorithms with a statistical relevant number of data sets.

References

[1] K. Herfarth, J. Debus, F. Lohr, M. Bahner, B. Rhein, P. Fritz, A. H"oss, W. Schlegel, M. Wannenmacher, Stereotactic Single Dose Radiation Therapy of Liver Tumors: Results of a Phase i/ii Trial, Journal of Clinical Oncology 19 (2001) 164–170.

[2] A. Erdi, Y. Hu, C. CS, Using mutual information (mi) for automated 3D registration in the pelvis and thorax region for radiotherapy treatment planning, in: Medical Imaging: Image Processing, Vol. 3979, SPIE, 2000, pp. 416–425.

[3] C. Studholme, D. Hill, D. Hawkes, An Overlap Invariant Entropy Measure of 3D Medical Image Alignment, in: Pattern Recognition, Vol. 32, 1999, pp. 71–86.

[4] F. Bookstein, Principal Warps: Thin-Plate Splines and the Decomposition of Deformations, in: IEEE Transactions On Pattern Analysis and Machine Intelligence, Vol. 11 No. 6, 1989, pp. 576–585.

[5] B. Likar, F. Pernus, A Hierarchical Approach to Elastic Registration Based on Mutual Information, in: Image and Vision Computing, 1999, pp. 33–44.