AUTOMATED LANDMARK DETECTION FOR RIGID REGISTRATION BETWEEN THE SIMULATION-CT AND THE TREATMENT CBCT

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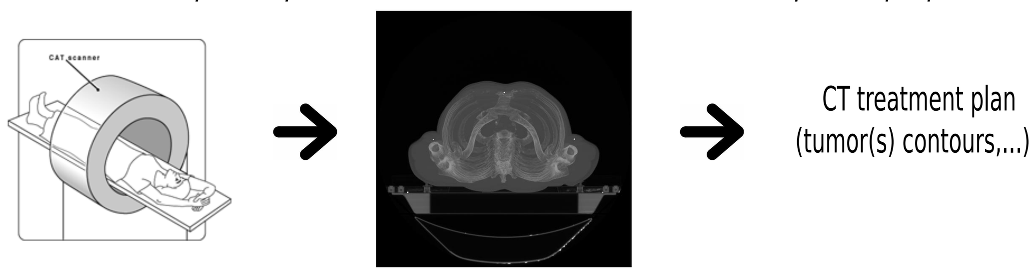
Aims

We propose a new machine learning based registration algorithm able to approximate current state-of-the art methods for CT-on-CBCT registration without presenting common defaults of these methods. We thus compare our method to current state-of-art algorithms and manual registration.

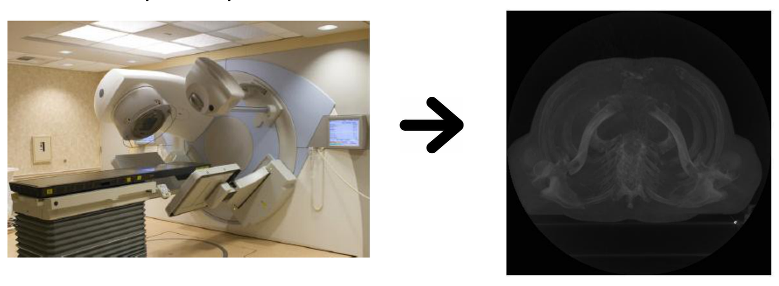
1. Why CT-on-CBCT registration?

First step : the patient comes for a CT and a treatment plan is prepared

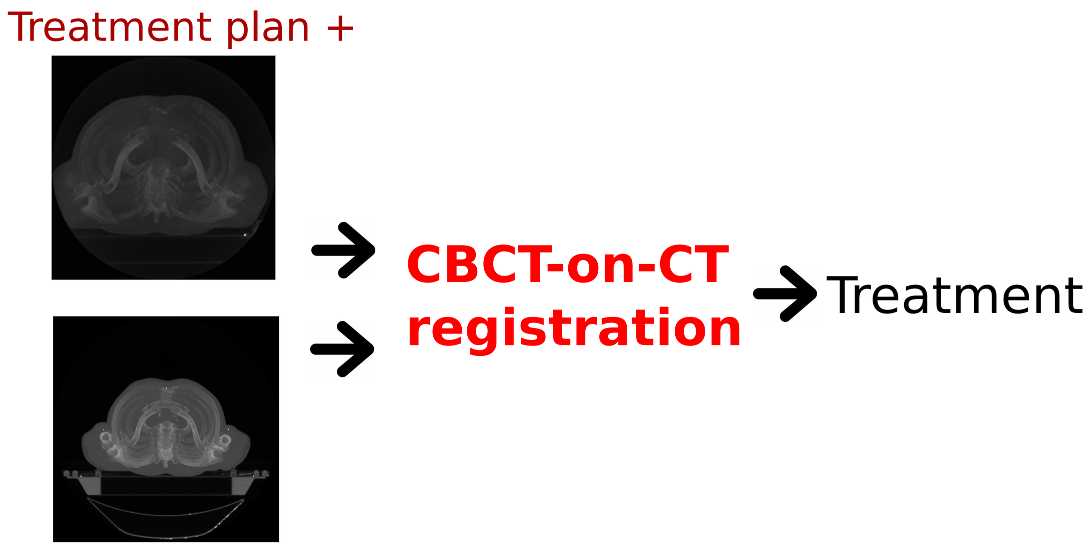


In the medical radiotherapy routine, a simulation CT-scan is first acquired: This simulation scan is used as the reference for the computation of the treatment plan.

Second step: the patient comes for his treatment and take a CBCT



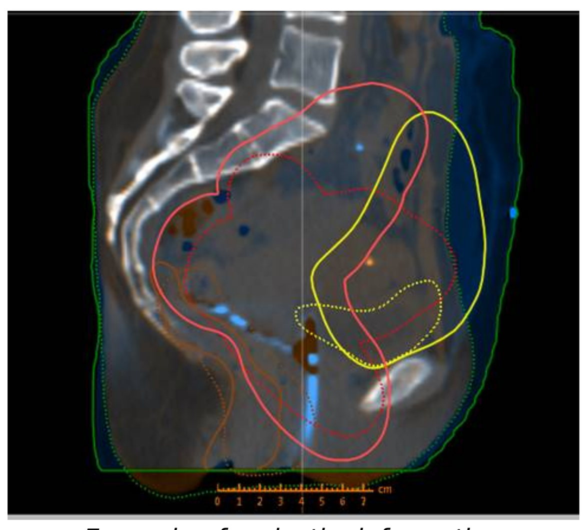
Then, for many cancer locations, before each treatment session, a CBCT-scan is acquired, so as to place the patient at the reference position of the computed treatment plan. This positioning is done through image registration.



CBCT-on-CT registration is thus a very important step: a wrong registration would imply a bad positioning of the patient and so an inefficient and possibly damaging radiotherapy treatment

2. Main challenges

Solving this problem properly requires to address several challenging questions:



Example of a plastic deformation

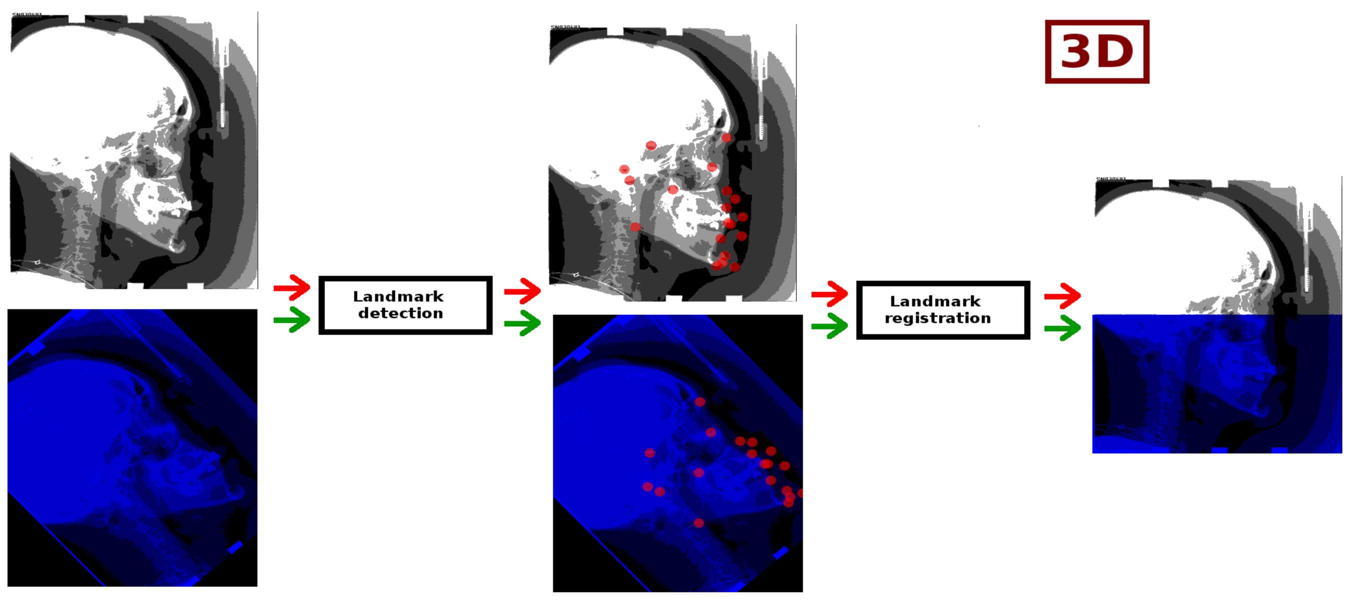
1) Most registrations are rigid and only applies rotations and translations, while bodies deformations are plastic. Therefore, for optimal registration, we should apply plastic deformation.

2) CBCT and CT are not the same modality nor the same resolution: it means that the pixel value of one pixel located in a specific place (ie, a bone), will not be the same between the two images. This is a source of problems, because it becomes more difficult to express the similarity between a CT and a CBCT, which is very important in image registration.

3) There are clear problems of interoperability and transmission of image data between different softwares. Most of the time, each medical imaging software has its own, proprietary, closed registration process. This makes algorithmic comparisons extremely complicated to perform

3. Our Approach

In 2D imaging, a new approach based on landmark detection and registration has proven to be a very interesting way to register images. Our goal is translate this approach in 3D medical imaging. We want to automate landmark detection with an algorithm able to predict landmark coordinates in new volumes and compute their rigid deformations.



This approach is based on the automation of a manual registration procedure: the operator selects a sufficient number of corresponding landmarks on both images or volumes, and then, given the coordinates of those landmarks, a simple linear algbera procedure can be used to find the deformation. The real problem will thus be to automatically detect the landmarks.

We used a methodology based on machine learning: given a dataset of pairs of points (represented by point descriptors) and their corresponding distances to a landmark, we built a model able to predict the distance between the points and the landmark in new volumes. Once this model is built, the position of the landmark in a new volume will be the position of the point predicted as the closest to the landmark.

4. The Algorithm

Following our previous work ([1],[2]), we adopted a supervised learning approach that exploits the manually annotated volumes to train models able to predict landmark positions in new, unseen images. In particular, a separate voxel regression model is trained to predict the distance between the position of a given voxel and the position of the landmark. This model is trained from a learning sample composed of voxels extracted either in the close neighboorhood of of the landmark or at other randomly chosen positions within the training volumes. Voxels are described by sums of neighboring voxels, following the work of [3]. The landmark position in a new volume will be the position of the voxel predicted as the closest to the landmark.

Naively sampling voxels uniformly from the training volumes will give a very unbalanced dataset, given that high accuracy is needed for voxels close to the landmark, and rough estimations are sufficient for voxels far from the landmark. To generate a more balanced dataset, we randomly select N pixels in each volume, where 33% of these pixels are selected in a maximal radius of R (~10-15mm) to the landmark, and the 67% are selected elsewhhere in the volume.

Once the landmark positions are found on both the CT and the CBCT, it is thus possible to find the optimal rigid deformation matrix through SVD decomposition.

5. Data and results

We performed our study using 51 pairs of pelvis CT-CBCT coming from 29 different patients, where we manually annotated 8 landmarks. For each patient, we detected the landmarks positions on its volumes using the dataset coming from the 28 other patients (leave-one-out).

The mean accuracy of our landmark detection was between 4.5 and 6 voxels for CBCT, and between 2.9 and 3.3 voxels for CT (IC 99%). We explain this difference by the higher resolutions of our CBCTs, where the voxels size is 1x1x1mm, while typical CT resolution is 1.6x1.6x5mm: low resolution voxels are easier to detect for our algorithm, but they give less information about their real position.

We compared our algorithm to the registration results coming from the Elastix software [4] and the manually annotated landmark registration. Using the manual image registration, the mean distance between the annotated landmarks was between 4.42 and 5.26mm, Elastix results between 6.14 and 14.12mm while with our automated landmark registration the error was between 7.92 and 9.59mm (IC 99%).

We think that a large part of this error comes from the low resolution volumes: a 2 voxel error on the CT results in an error >10mm. For the Elastix registration, we noticed it was outperformed by our algorithm when the volumes were separated by a large deformation (>50~60mm),

6. Conclusion

In this work, we showed very promising results for automated landmark detection on 3D volumes in terms of voxel accuracy. Given the resolutions of our scans, we consider our registration results as really interesting and competitive to current state-of-the art registration algorithms.
The main advantage of our algorithm compared to state-of-the art methods is that the performances of the registration will not depend on the initial proximity of the two volumes. Using the results of our algorithm as an initialization step prior to state-of-the-art registration methods could lead to fully automated and accurate registration methods.

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