

Automated Landmark Detection For Rigid Registration Between The Simulation CT and The Treatment CBCT

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Introduction

As a part of the RT process, CBCT-scans are acquired on a daily basis, so as to place the patient at the reference position of the computed treatment plan: This positioning is done through rigid image registration wrt. the simulation CT-scan. The golden standard of algorithms for the registration of 3D images are inherently iterative and based on the value of the voxels. In the context of 2D images, it is now well known that rigid registration can be dramatically improved and accelerated by detecting, then matching highly informative spots in the images that are known as “landmarks”. Our goal is to transpose this 2D approach to real-world 3D medical imaging by introducing novel, automated algorithms for landmark detection in 3D images.

Materials and Methods

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 neighborhood 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 Criminisi et al.^[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 elsewhere 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. A graphical depiction of our method is presented in Figure 1.

We performed our study using 51 pairs of pelvis CT and CBCT from 29 patients, where we manually annotated 8 landmark in each modality. Two detection models were built: one for the CT and one for the CBCT modality. For each patient, we detected the position

of each landmark using a model trained from the images of the 28 remaining patients, then we performed rigid registration across modalities using these landmark through simple linear algebra. The accuracy of both landmark detection and registration was then evaluated and averaged over the 29 patients. Registration accuracy is measured by the averaged distance, over all 8 landmark, between the (true) position of the landmark in CT and in CBCT after registration.

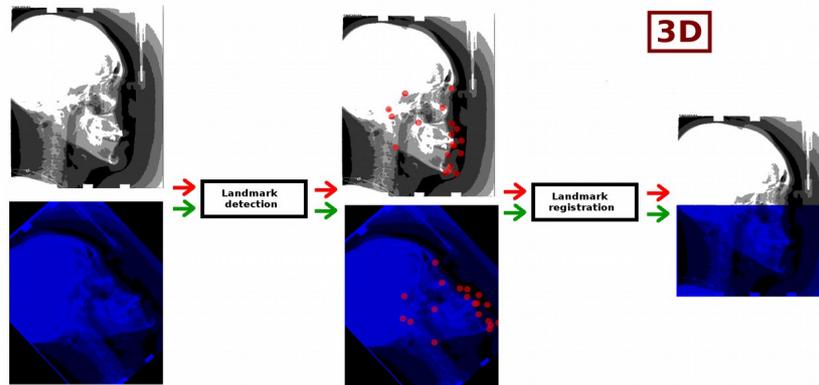


Figure 1 : Illustration of the method

Results and Discussion

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).

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.

References

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