

# QUALITY ASSESSMENT OF NON-RIGID REGISTRATION METHODS FOR ATLAS-BASED SEGMENTATION IN HEAD-NECK RADIOTHERAPY

*Adriane Parraga, Altamiro Susin*

*UFRGS  
Dept. Electrical Engineering  
Av. Osvaldo Aranha 103, 206-B  
Porto Alegre/RS  
Brazil*

*Johanna Pettersson*

*Linköpings Universitet  
Dept. of Biome. Engineering  
Medical Informatics  
S-581 85 Linköping  
Sweden*

*Benoit Macq, Mathieu De Craene*

*Université Catholique de Louvain  
Communication and Rem. Sen. lab.  
Place du Levant, 2  
B-1348 Louvain-la-Neuve  
Belgium*

## ABSTRACT

In this paper we compare three non-rigid registration methods for atlas-based segmentation: B-Splines, Morphons and a combination of Morphons and Demons. To assess the quality of each method, we use a data set of four patients, containing for each patient the Computed Tomography (CT) image and a manual segmentation of the organs at risk performed by an expert of the head and neck anatomy. Non-rigid registration algorithms have been used to match the patient and atlas images. Each deformation field, resulting from the non-rigid deformation, have been applied on the masks corresponding to segmented regions in the atlas. The atlas based segmented masks have been compared to manual segmentations performed by the expert. The results show that the combined method (Morphons + Demons) achieves the best performances on this dataset resulting in an average improvement of 6% with respect to Morphons and 18% with respect to B-spline.

**Index Terms**— image registration, image segmentation, biomedical imaging processing

## 1. INTRODUCTION

Intensity Modulated Radiotherapy (IMRT) is a new technique enabling the sculpting of the 3D radiation dose. It allows to sculpt a radiation zone of almost any shape and to modulate the beam intensity inside the target. If IMRT enables to constrain the radiation plan in the beam delivery as well as in the protection of important functional areas (e.g. spinal cord), it also raises the issues of adequacy and accuracy of the selection and delineation of the target volumes. The delineation in the patient CT image of the tumor volume and organs to be radio-protected is most of the time performed by a specialist who delineates slice by slice the contours of interest. This task is highly time-consuming and requires experts' knowledge. Moreover, intra- and inter-observer variability of the delineation may induce a lack of reproducibility. For all these reasons, the development of automatic segmentation methods based on atlases is a promising paradigm for speeding up the delineation process and reducing its variability.

Registration is useful in several medical applications such as segmentation, to build statistical atlas, for planning and to follow-up treatment. For applications such as radiotherapy treatment, an intra-patient registration is necessary since the anatomy of the patient changes during treatment. This task becomes much more com-

plicated when we have to register an atlas (typically chosen as a representative patient manually segmented) with another patient. Inter-subject image registration methods have been the subject of extensive study in many areas of medical imaging applications, but most efforts have been in atlas-driven segmentation of the brain [1], [2], [3]. Also, many previously presented methods are related to 2D dataset or they are not totally automatic since they are based on landmarks.

Here we focus on the clinical application of head and neck tumors for 3D automatic atlas-based segmentation. For assisting the radiologist in the segmentation task, we investigate which registration method is the most suitable, also taking into account the pathological and anatomical variations. The imaging modality mainly used in this application is the Computed Tomography (CT) because of its excellent anatomical resolution. We bring an atlas (segmented image of a sane individual) into alignment with the CT image of the patient. This atlas registration problem is made particularly challenging by the presence of tumors in the patient image, which induces changes in the anatomy of the patient. Several registration methods have been applied and validated for atlas-based segmentation of the brain (like for instance B-splines and Demons).

In this paper we first compare two methods, B-splines [4], [5] and Morphons [6], [7]. While the former has already been explored in the literature for some time, the later is an emerging feature based registration method. We have also investigated a combination of Morphons and Demons [8]. To assess the quality of each method, we have taken a set of patient's 3D images, which have previously been segmented by a doctor with the organs to be protected for radiotherapy planning, called organs at risk (OAR). An affine registration is followed by a dense non-rigid deformation step. Each deformation field, resulting from the non-rigid deformation, has been applied on the masks corresponding to segmented regions in the atlas. The performance of each method has been measured by an overlap measure between the patient's and the deformed atlas' masks. In the next section we briefly described the registration methods used in this work. In Section 3, we describe some details of the implementation and the metric used and also illustrates the results of the qualitative analysis. Finally, discussions and conclusions are presented in Section 4.

## 2. IMAGE REGISTRATION ALGORITHMS

This section briefly describes the registration algorithms used in this work. Registration is the process of finding a transformation  $T$  that

best matches two images according to a criterion of similarity. One image is the reference, which remains fixed during the registration process, while the other is deformed in the geometric space of the reference. The reference image is also called "fixed or target image" and the transformed image is called the "moving image".

### 2.1. B-spline registration

B-spline is a non-rigid registration algorithm that has been widely used in the past few years. The transformation model is a free-form deformation (FFD) that is described by a cubic B-spline [4], [9].

$$T(x, y, z) = \sum_{l=0}^3 \sum_{m=0}^3 \sum_{n=0}^3 \beta_l(u) \beta_m(v) \beta_n(w) \phi_{i+l, j+m, k+n} \quad (1)$$

The parameter  $\phi_{i,j,k}$  is the set of the deformation coefficients which is defined on a sparse, regular grid of control points placed over the moving image.

For any point  $x, y$  and  $z$  of the moving image, the B-spline transformation is computed from the positions of the surrounding  $4 \times 4 \times 4$  control points. The  $i, j$  and  $k$  are the indices of the control points and  $u, v$  and  $w$  are the relative positions of  $(x, y, z)$  inside that cell in the 3D space.

The functions  $\beta_0$  through  $\beta_3$  are the third-order spline polynomials. More details related to B-spline based registration can also be found in [10].

### 2.2. Morphons registration

Registration with Morphons [6] involves iterative accumulation of a dense deformation field under the influence of certainty measures. These certainty measures are associated with the displacement estimates found in each iteration.

$$\vec{d}'_a = \frac{c_a \vec{d}_a + c_k (\vec{d}_a + \vec{d}_k)}{c_a + c_k} \quad (2)$$

where  $\vec{d}'_a$  indicates the *updated* accumulated deformation field,  $\vec{d}_a$  is the accumulated field from the previous iteration and  $\vec{d}_k$  is the displacement estimates derived in the current iteration (described below).  $c_a$  and  $c_k$  are certainty estimates associated with the accumulated deformation field and the displacement estimates, respectively.

The displacement estimates are found from local phase difference. A set of quadrature filters, each one sensitive to structures in a certain direction, is applied to the target and atlas respectively. The output of one quadrature filter is:

$$q = (q * s)(\vec{x}) = A(x) e^{i\phi(x)}$$

The phase difference between two signals can be found according to:

$$q_1 q_2^* = A_1 A_2 e^{i\Delta\phi(x)} \quad (3)$$

The phase difference is the argument of this product,  $\Delta\phi(\vec{x}) = \phi_1(\vec{x}) - \phi_2(\vec{x})$ . The local displacement estimate  $d_i$  in a certain filter direction  $i$  is proportional to the local phase difference of the filter responses in that direction,  $d_i \propto \Delta\phi(\vec{x})$ . A displacement estimate is found for each pixel and for each filter in the filter set. Thus, a displacement field  $d_i$  is obtained for each filter direction  $\vec{n}_i$ . These fields are combined into one displacement field by solving a least square problem:

$$\min_{d_k} \sum_i [c_i (\vec{n}_i^T \vec{d}_k - d_i)]^2$$

where  $\vec{d}_k$  is the sought displacement field,  $\hat{n}$  is the direction of filter  $i$ , and  $c_i$  is the certainty measure (equal to the magnitude of equation 3).

### 2.3. Demons registration

The Demons registration method is based on intensity changes and is driven by the concept of optical flow [8]. Optical flow calculates velocity from temporal sequences of images, accordingly to the expression:

$$\vec{v} = \frac{(m - f) \vec{\nabla} f}{|\vec{\nabla} f|^2 + (m - f)^2} \quad (4)$$

In 4,  $\vec{v}$  is the optical flow velocity and  $m$  and  $f$  are two consecutive time frames. In the inter-patient registration problem there is no such temporal consideration. So,  $\vec{v}$  is considered to be as a displacement for each pixel at the moving image towards the fixed image.

## 3. RESULTS

### 3.1. Dataset

A set of four 3D CT patients previously segmented by a doctor has been used to assess the registration methods for atlas-based segmentation. The size of the CT volumes is of  $256 \times 256 \times 128$  pixels with a voxel size of  $0.9765 \times 0.9765 \times 2.1093 \text{ mm}^3$ . In radiotherapy planning, the following structures are segmented during the treatment planning phase: external body contours, organs at risk (parotid glands and spinal cord), the region along with the tumor (nodal clinical target volume CTV-N). The delineation of CTV-N is performed because of the risk of microscopic extension of the tumors and/or nodes in the fatty tissues.

### 3.2. Implementation

First, the patient volumes and the atlas have been segmented, resulting in a contour of the regions previously described. From each contour a binary mask has been created, setting ones inside the contour and zeroing the remainder of the grayscale image. An affine transformation of the atlas has been applied, bringing the atlas into a geometric alignment with the patient. Then, non-rigid registration methods have been performed, resulting in dense deformation fields, which have been then applied to the masks of the atlas. The atlas' masks registered to the patient are the segmented regions sought. To evaluate the segmentation, we compared the resulting masks with the manual segmentation performed by a doctor.

The metric used to measure spatial intersection of two binary images (masks) was the similarity index (SI) [11].

$$SI = 2 \cdot \frac{|M_P \cap M_A|}{|M_P| + |M_A|} \quad (5)$$

where  $|\cdot|$  is the number of non-zero pixels of the masks and  $SI \in [0, 1]$ . The perfect match between the masks gives  $SI = 1$  and the worst case, i.e. totally mismatch,  $SI = 0$ .  $SI$  was calculated between the masks of the patient,  $M_P$ , and the masks of the atlas being registered to the patient,  $M_A$ , as in eq. 5. The similarity index defined in eq. 5 has been introduced in the area of image segmentation to measure the agreement between different classifications[12].

The registration process was implemented in the ITK Registration framework for the B-spline and Demons algorithms and in Matlab for the Morphons. For Demons registration we have used the

**Table 1.** Similarity index for Patient 10 and atlas

	B-spline	Morphons	Morphons Demons
Body	0.97	0.96	0.98
CTV N Left	0.60	0.65	0.73
CTV N Right	0.59	0.64	0.66
Left parotid	0.63	0.70	0.76
Right parotid gland	0.61	0.70	0.75
Spinal Cord gland	0.69	0.73	0.79

**Table 2.** Similarity index for Patient 04 and atlas

	B-spline	Morphons	Morphons Demons
Body	0.93	0.96	0.98
CTV N Left	0.43	0.58	0.64
CTV N Right	0.36	0.41	0.42
Left parotid gland	0.46	0.50	0.50
Right parotid gland	0.41	0.45	0.47
Spinal Cord (sc)	0.66	0.82	0.78

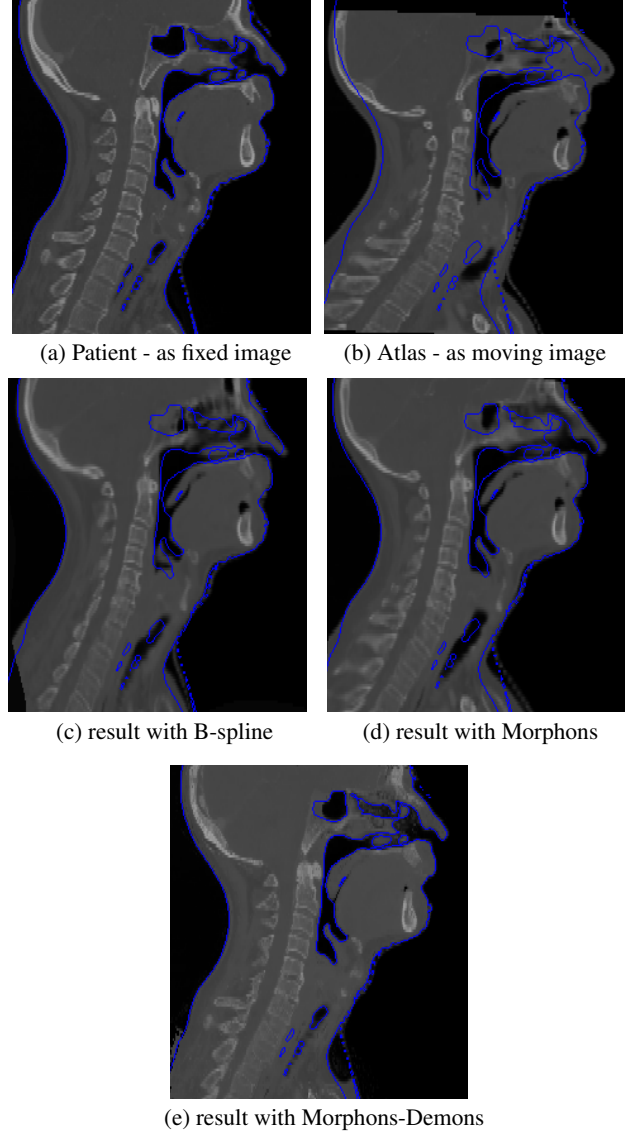
**Table 3.** Similarity index for patient 09 and atlas

	B-spline	Morphons	Morphons Demons
Body	0.96	0.97	0.98
CTV N Left	0.57	0.61	0.68
CTV N Right	0.52	0.61	0.67
Left parotid gland	0.62	0.70	0.80
Right parotid gland	0.71	0.74	0.78
Spinal Cord (sc)	0.66	0.73	0.79

*itk::SymmetricForcesDemonsRegistrationFilter* class. For ITK see (<http://www.itk.org>).

To refine the results, we use Demons with a good initialization of the deformation field. So, the last registration method we have tested is a combination of Morphons and Demons, initializing the Demons with the deformation field arriving from the Morphons registration. Tables 1, 2 and 3 show the *SI* between the patients' and atlas' masks. Fig. 1 shows one slice of the volumes with a sagittal view of the patient, atlas and the results. Fig. 1(a) is the patient and also the fixed image in the registration process. Fig. 1(b) is the atlas being registered to the patient. Fig. 1(c), 1(d) and 1(e) are the results using B-spline, Morphons and Morphons-Demons, respectively. Fig. 2 has also one slice of the volumes of the patient, atlas and the results, but with the axial view.

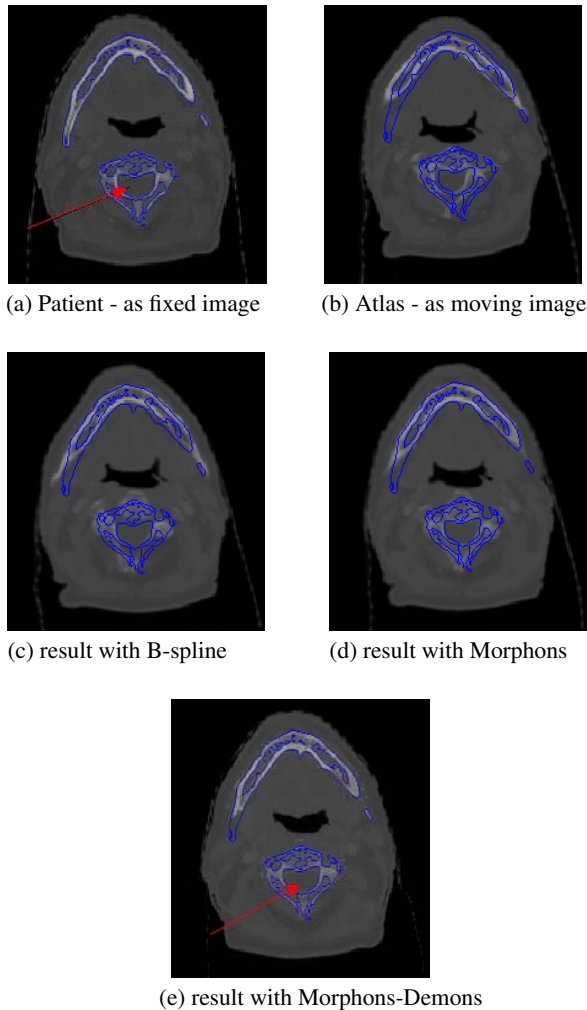
To better compare the images, we have traced a blue contour over the patient image and superimposed it over the other ones. The *SI* values show that the Morphons method has performed better when comparing it with B-splines. The resulting images have been qualitatively validated by a doctor, who has confirmed that the bones are better aligned with the Morphons and Demons-Morphons, and consequently the spinal cord, indicated by a red arrow in Fig. 2(a) and Fig. 2(e). This is because of the high contrast of the bones. The segmentation has improved with the proposed combination algorithms in average 6% in relation to the Morphons and in 18% better than B-spline.



**Fig. 1.** Non-rigid registration results showing a sagittal view of one slice from 3D dataset of head and neck region (a) patient as fixed image and also as the reference with the blue contour over other slices (b) atlas as a moving image (c) registered atlas using B-splines algorithm (d) registered atlas using Morphons algorithm (e) registered atlas using Morphons and Demons algorithms.

#### 4. DISCUSSIONS AND CONCLUSIONS

In this paper we have proposed a two steps strategy for addressing the problem of inter-subject registration. This task is particularly hard to accomplish when we try to register 3D patient volumes with a very different anatomy, as in the case of atlas to patient registration. Figures 1(a) and 1(b) show the volumes dissimilarity representing the anatomical variability of the population. To choose the most suitable algorithm for atlas-based segmentation in the context of head and neck radiotherapy, we compared quantitatively 3 non-rigid registration methods: Morphons, Demons and B-splines. Morphons performs better for matching all structures being considered when



**Fig. 2.** Non-rigid registration results showing an axial view of one slice from the 3D dataset of head and neck region (a) patient as fixed image and also as the reference with the blue contour over other slices (b) atlas as a moving image (c) registered atlas using B-splines algorithm (d) registered atlas using Morphons algorithm (e) registered atlas using a combination of Morphons and Demons algorithms.

comparing with B-splines, improving in average 10% the segmentation. To improve our results, we have passed the deformation field obtained by Morphons algorithm as an initialization to Demons. The registration has also been validated by an expert, which has found the results, qualitatively speaking, very good. The quality of the registration can also be observed in figure 1(e) and 2(e), where the combined methods exhibits much better alignment visually. Because of their high contrast, bones can drive the registration of adjacent structures like spinal cord. Extension of these results to more cases will be considered as future work. The improvement in terms of overlapping indexes between manual and atlas-based segmentation results let us think that the combined Morphons + Demons approach is both robust and accurate. Another extension of this work will replace our deterministic atlas by a probabilistic atlas such as described in [13]

for the brain.

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## 6. REFERENCES

- [1] M. Ferrant, O. Cuisenaire, and B. Macq, "Multi-object segmentation of brain structures in 3d mri using a computerized atlas," in *SPIE Medical Imaging*, 1999.
- [2] M. B. Cuadra, C. Pollo, A. Bardera, O. Cuisenaire, J. Villemure, and J.-P. Thiran, "Atlas-based segmentation of pathological mr brain images using a model of lesion growth," *IEEE Trans. Med. Imaging*, vol. 23, no. 10, pp. 1301–1314, 2004.
- [3] C. Pollo, M. B. Cuadra, O. Cuisenaire, J. Villemure, and J. Thiran, "Segmentation of brain structures in presence of a space-occupying lesion," *Neuroimage*, vol. 24, no. 4, pp. 990–996, February 2005.
- [4] D. Mattes, D. R. Haynor, H. Vesselle, T. K. Lewellen, and W. Eubank, "Pet-ct image registration in the chest using free-form deformations," *IEEE Trans. Med. Imaging*, vol. 22, no. 1, pp. 120–128, 2003.
- [5] D. Rueckert, A. F. Frangi, and J. A. Schnabel, "Automatic construction of 3d statistical deformation models of the brain using non-rigid registration," *IEEE Trans. Med. Imaging*, vol. 22, no. 8, pp. 1014–1025, 2003.
- [6] A. Wrangsj, J. Pettersson, and H. Knutsson, "Non-rigid registration using morphons," in *Proceedings of the 14th Scandinavian conference on image analysis (SCIA'05)*, Joensuu, June 2005.
- [7] H. Knutsson and M. Andersson, "Morphons: Segmentation using elastic canvas and paint on priors," in *IEEE International Conference on Image Processing (Proceedings of the IEEE International Conference on Image Processing'05)*, Genova, Italy, September 2005.
- [8] J.-P. Thirion, "Image matching as a diffusion process: an analogy with maxwell's demons," *Medical Image Analysis*, vol. 2, no. 3, pp. 243–260, 1998.
- [9] D. Rueckert, L. I. Sonoda, C. Hayes, D. L. G. Hill, M. O. Leach, and D. J. Hawkes, "Non-rigid registration using free-form deformations: Application to breast mr images," *IEEE Trans. Med. Imaging*, vol. 18, no. 8, pp. 712–721, 1999.
- [10] T. Rohlfing, R. Brandt, C. R. Maurer, Jr., and R. Menzel, "Bee brains, B-splines and computational democracy: Generating an average shape atlas," in *IEEE Workshop on Mathematical Methods in Biomedical Image Analysis*, 2001.
- [11] B.M. Margolin R.A. Palmer A.C. Zijdenbos, A.P. Dawant, "Morphometric analysis of white matter lesions in MR images: method and validation," *IEEE Transactions on Medical Imaging*, vol. 13, no. 4, pp. 716–724, decembre 1994.
- [12] L. Zhang, E. Hoffman, and J. M. Reinhardt, "Lung lobe segmentation in volumetric X-ray CT images," *IEEE Trans. Medical Imaging*, vol. 25, no. 1, pp. 1–16, 2006.
- [13] A. C. Evans, D. L. Collins, and B. Milner, "An mri-based stereotactic atlas from 250 young normal subjects," *Journal Soc. Neurosci. Abstr.*, vol. 18, pp. 408–492, 1992.