Improving thoracic elastic registration in oncology by using anatomical constraints

Oscar Camara[a,b]*, Gaspar Delso[a], Vincent Frouin[c] and Isabelle Bloch[a]

[a]Département Signal et Images, CNRS URA 820, ENST, Paris[b] Segami Corporation, France
[c]Service Hospitalier Frédéric Joliot, CEA, 91401 Orsay, France

Abstract. The aim of the work presented here is to improve data analysis in thoracic oncology applications by means of non-rigid registration of CT and PET images. A transformation using B-Spline Free-Form Deformations (FFD) has been chosen to perform the alignment of the image volumes. The variability of the organ displacements in the mentioned areas justifies the choice of FFD, but special constraints must be added to grant the convergence towards a proper registration. In the proposed approach these constraints rely on hierarchically identifying corresponding structures in both modalities, which give us an initial estimation of the transformation between images.

1 Introduction

PET (Positron Emission Tomography) acquisition with 18-FDG tracer is becoming the reference image modality in oncologic applications. This imaging technique has shown to provide high sensitivity and specificity for the detection of primary and metastatic cancers not visualized by classical morphological acquisitions. However, it provides little information on the exact locations of the increased uptake. On the other hand, CT, which is the classical diagnostic modality in oncology, provides accurate details of the size and shape of lesions, but indicates nothing about lesion malignancy. Consequently, combining information from these two modalities would have a significant impact in improving medical decisions for diagnosis, therapy and treatment planning [1].

Integrating data from different imaging modalities requires geometric alignment or registration to compensate for differences in field of view, patient positioning and other acquisition parameters. Several difficulties arise from the different acquisition protocols and physical properties of the modalities to register, such as different sizes, resolutions, scan times or patient position. In our particular case, these problems specially worsen due to the elastic nature of the imaged regions, as it is shown in Fig. 1.

In many cases a satisfactory solution can be found by using rigid or affine registration. However, in thoracic and abdominal applications, due to local deformations and the high variability of acquisitions, a non-rigid approach with significantly more degrees of freedom is needed.

To the best of our knowledge, little effort had been made in the past to register very deformable anatomical regions such as the thorax and abdomen. However, several recent research works aim at registering these regions. One elegant solution to multimodality chest image registration was proposed by Mattes [2]. He models deformations with cubic B-Splines defined by placing a regular grid of control points over the volume and then modified by moving these control points. Mutual information, proposed by Viola [3] is used to measure image similarity.

Our work is based on an evolution of this technique used by Rueckert et al. [4] for the non-rigid registration of contrast-enhanced breast MRI. The results indicate that this registration algorithm is much more able to recover the motion and deformation of the breast than rigid or affine registration algorithms. A drawback of this method was the excessive power of the transformation, that tended to converge towards local minima of the similarity criterion unless a very accurate initialization was provided.

One way to provide such an initialization may be obtained through the extraction of anatomical references. In this paper we propose a method in which, by turning the initialization procedure into almost an elastic registration of its own, we are able to effectively apply an accurate Mutual Information registration technique to areas with severe deformations such as the thorax.

*Oscar.Camara@enst.fr

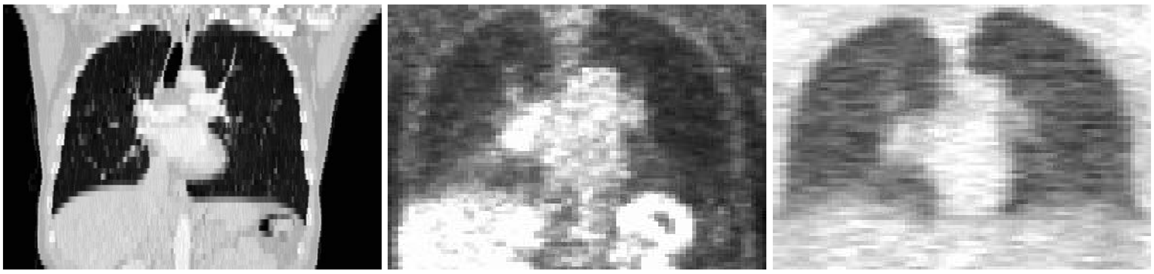

Figure 1. Coronal slices of original data volumes. Left: CT. Center: Attenuation PET. Right: Transmission PET

2 Registration Framework

Our goal has been to improve data analysis in various oncology applications by means of non-rigid registration of CT and PET images. A non-rigid transformation using B-Spline Free-Form Deformations (FFD) [5] has been chosen to perform the registration of the image volumes. The justification of this choice lies in the variability of the displacements of the organs, that makes it unpractical to choose a more constrained parametric model. On the other hand, the speed requirements of this application forbid the use of more complex deformation schemes, like elastic or fluid models. In this technique, deformations of the object volume are achieved by tuning an underlying mesh of control points. The control point displacements are then interpolated to obtain a smooth and continuous *C2* transformation. A B-Spline based FFD can be written as a 3D tensor product of one-dimensional cubic B-Splines. Let Φ denote an uniformly spaced grid of $n_x \times n_y \times n_z$ control points $\phi_{i,j,k}$ with a spacing of δ, where $-1 \leq i < n_x - 1, -1 \leq j < n_y - 1, -1 \leq k < n_z - 1$. Then, the elastic transformation for each image point *x,y,z* is computed:

$$T_{elast}(x, y, z) = \sum_{l=0}^{3} \sum_{m=0}^{3} \sum_{n=0}^{3} B_l(u) B_m(v) B_n(w) \phi_{i+l,j+m,k+n} \tag{1}$$

Here, *i*, *j*, and *k* denote the index of the control point cell containing *(x,y,z)*, and *u*, *v*, and *w* are the relative positions of *(x,y,z)* in the three dimensions, B_0 through B_3 being 1D cubic B-Splines. A very convenient property of B-Splines is the fact that they have a limited support, thus providing us with local control of the transformation, which contributes to reduce significantly the amount of computation needed during the optimization process. The displacement of the control points is found by optimizing a similarity measure, a function that evaluates the quality of the registration for a given set of transformation parameters.

The choice of a similarity measure is strongly related to the imaging modalities to be registered. Due to the non-functional relation between CT and PET representations of the same tissues we use Normalized Mutual Information (NMI), a variant of the Mutual Information criterion. Normalised Mutual Information was introduced in [6] to prevent the actual amount of image overlap to affect the measure. Normalized Mutual Information is an information theoretic measure that expresses how much information from an image A is contained by another image B.

$$NMI(A, B) = \frac{H(A) + H(B)}{H(A, B)} \tag{2}$$

Where *H(A)* and *H(B)* are the marginal entropies of images and *H(A,B)* is their joint entropy, which is calculated from the joint histogram of *A* and *B*.

The main drawback of this method is that it tends to get trapped in local minima of the similarity function. One way to overcome this limitation is to provide a good enough initialization of the deformation field, based on whatever structural information can be extracted from the images.

3 Initialization procedures based on segmentation of anatomical structures

Detection of anatomical features is one of the most intuitive ways to register medical images, and has been used successfully in a wide variety of applications. Plenty of examples can be found in the literature of methods relying on paired landmarks to perform the registration, or searching to minimize the distance between organ contours or surfaces. However, this kind of techniques have a serious drawback in the fact that they rely on a segmentation step to provide them with the anatomical references they need. Consequently, any errors introduced by the segmentation will affect the accuracy of the final registration. On the other hand, using one of this methods could provide a fast and reliable initialization for the non-rigid transformation and a certain set of constraints, leaving the subsequent

Mutual Information-based registration to deal with any inaccuracies stemming from the segmentation error, as well as with those structures that could not be automatically segmented.

A good trade-off between speed and quality of segmentation has been achieved by means of a hierarchical procedure consisting of several segmentation steps aimed at progressively classifying different anatomical structures, using the information obtained from the most disctinct features to restrict the segmentation of subtler ones. Consecutive steps to detect elements of increasing difficulty will rely on the different spatial constraints that can be inferred from the already segmented structures with the target organ. The idea of progressive structure recognition was already used in [7] for cerebral tissue classification.

Each segmentation step consists of several thresholding stages alterned with mathematical morphology operations. Certain criteria including dimensions, volume and others simple measures have been defined to verify whether the organ has been properly detected or not, in order to adapt the segmentation parameters to the most common anatomical variations. Although this approach might seem somewhat inaccurate, it must be kept in mind that there is a full Mutual Information-based registration procedure to take care of the fine tuning of the results. Our priorities here are rather speed and robustness, for which this approach has proven more than convenient.

The automatic thresholding is performed by a k-means algorithm. Two dimensional vectors for the voxels are used for the PET image, to take advantadge of the information contained both in the transmission and attenuation images. Additionally, this helps to compensate for the small variations between both acquisitions.

Once the visible structures have been segmented and set in a common metric space, their contours are extracted and brought into rigid registration by means of the Iterative Closest Point algorithm (ICP). This algorithm has been widely used with good results since it was first introduced in [8]. Furthermore, the distance map computed for the ICP algorithm provides an efficient, if primitive, estimation of the non-rigid transformation between the surfaces of each pair of organs, that can be then generalized to the whole volume by means of a zero Laplacian condition. This can be used to initialize the positions of the control points of the free-form deformation that will be applied to the original images. Given this initialization, the speed and accuracy of the subsequent mutual-information based registration are significantly increased.

4 Results

Despite no gold standard parameter set being available to evaluate the performance of the registration, some quantitative measures can be applied to compare the results obtained with different techniques given a pair of input volumes. Two such measures have been used here: Normalized Mutual Information and the overlap ratio consisting of a quotient between intersection and union among segmented organs. Fig. 2 shows the results obtained for six data sets composed of CT, emission and transmission PET images of lung cancer patients provided by LifeScan Louisville and H.I.A. du Val-de-Grâce. A clear improvement of the results can be appreciated when the initialization procedure is applied. Note also that this improvement is more important in the overlap measure, as that is based on a segmentation of the registered images and does not account for the segmentation inaccuracies that may have been introduced by the initialization.

Visual inspection confirms these results, as can be appreciated in Fig. 3, where the lung contours of the registered PET image have been overlaid on the original CT. Notice how initialization has provided a better fit of the basically rigid top of the lungs, allowing a more accurate convergence of elastic moving parts, such as the diaphragm.

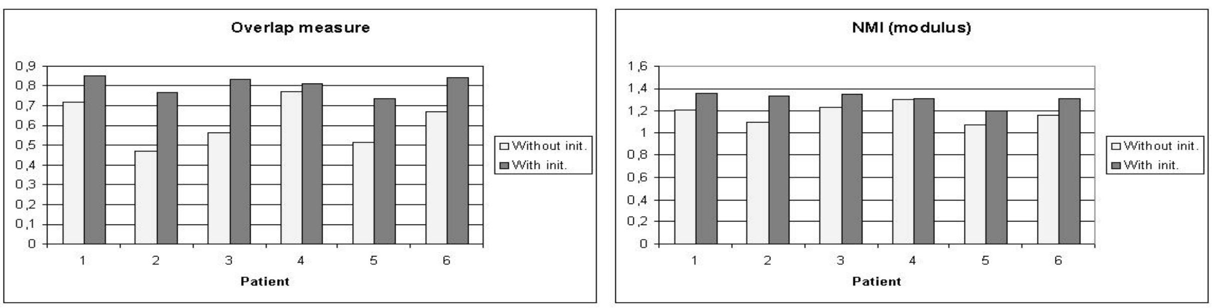

Figure 2. Measures of registration quality. Left: Overlap measure. Right: NMI modulus.

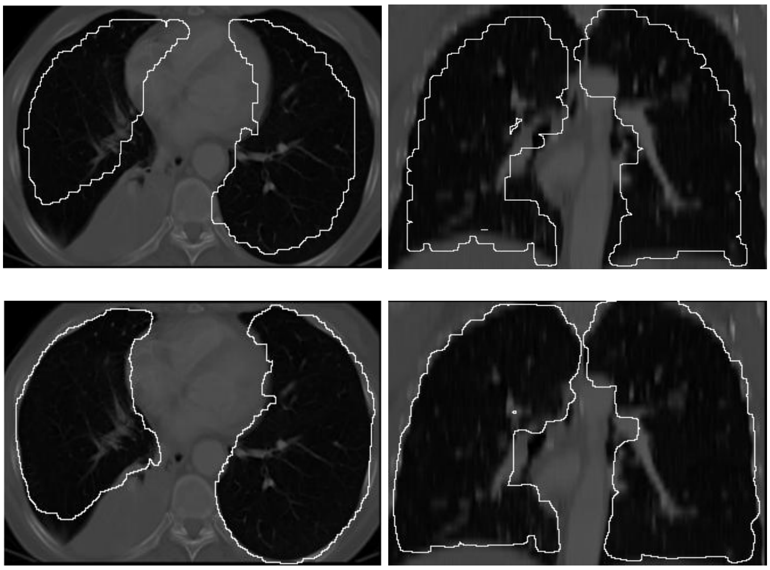

Figure 3. Registration results. Top: Without anatomical constraints. Bottom: With initialization procedure. Left: Axial slices. Right: Coronal slices.

5 Conclusions

The results presented in this paper indicate that our method can provide a reliable tool for data analysis in thoracic and abdominal oncology applications. The non-rigidity in the imaged regions is effectively modeled by means of a Free Form Deformation(FFD), and satisfactory registration results can be obtained by minimizing a Normalized Mutual Information criterion, given a good enough initialization. A progressive classification method has been proposed to provide such an initialization. Further work will focus on improving the integration of the different deformation fields computed for each recognized organ, to avoid incoherence and take into account the mechanical properties of the intermediate tissue.

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