B-spline based Free Form Deformation Thoracic non-rigid registration of CT and PET images

Davood Khodadad
Department of Medical Physics and Biomedical Engineering & Research Center for Science and Technology In Medicine & Exceptional Talents Development Center, Tehran University of Medical Science. Young Researchers Club of Islamic Azad University of Tabriz
Tehran, Iran
dkhodadad@razi.tums.ac.ir

Alireza Ahmadian, Mohammadreza Ay,Armaghan Fard Esfahani, Hossein Yousefi Banaem
Department of Medical Physics and Biomedical Engineering & Research Center for Science and Technology In Medicine & research institute for nuclear medicine, Tehran University of medical science
Tehran, Iran
ahmadian@sina.tums.ac.ir
Mohhamdreza_ay@sina.tums.ac.ir,
fardesfa@sina.tums.ac.ir, yousefih@razi.tums.ac.ir

Habib Zaidi
Division of Nuclear Medicine,
Geneva University Hospital, CH-1211
Geneva 4, Switzerland
Habib.zaidi@hcuge.ch

***Abstract*— Accurate attenuation correction of emission data is mandatory for quantitative analysis of PET images. One of the main concerns in CT-based attenuation correction(CTAC) of PET data in multimodality PET/CT imaging is misalignment between PET and CT images. The aim of this study, is to proposed a hybrid method which is simple, fast and accurate, for registration of PET and CT data which affected from respiratory motion in order to improve the quality of CTAC. The algorithm is composed of three methods: First, using B-spline Free Form Deformation to describe both images and deformation field. Then applying a pre-filtering on both PET and CT images before segmentation of structures in order to reduce the respiratory related attenuation correction artifacts of PET emission data. In this approach, B-spline using FFD provide more accurate adaptive transformation to align the images, and structure constraints obtained from prefiltering applied to guide the algorithm to be more fast and accurate. Also it helps to reduce the radiation dose in PET/CT by avoiding repetition of CT imaging. These advances increase the potential of the method for routine clinical application.**

Keywords- PositronEmission Tomography(PET), Computed Tomography(CT), Registration, thoracic, attenuation correction, B-spline, Free Form Deformation (FFD).

I. INTRODUCTION

Image registration is overlaying at least two set of images, reference image and float image in order to obtain a transformation between the images specially correspondence and coordinates from a reference image to coordinates of homologous point in a test image [1]. In image analysis and diagnostic clinical application field, in order to compare or integrate the information which is gained from various data sources like in multimodality systems, image from different time or different field of views and multichannel image restoration, registration is an important parts of process.

There is a frequent need to comparing images for analysis, visualization and diagnostic purposes in the biomedical domain. Application include monitoring tumor growth treatment verification (registration with annotated atlases) and motion detection(distortion).

Comprehensive survey of image registration methods was published in 1992 by Brown[1], others by J.B.A. Mantiz and M.A. Viergever [2], Zitova´ and flusser in 2003[3], and Vogel et al. in 2007[4].

The computed tomography (CT) scan of the thorax has been widely used for investigating and staging of lung tumors. It has the advantage of offering high resolution images with detailed anatomical structures, but its main drawback is lack of pathophysiologic information of the tumors [5]. In contrast to CT, positron emission tomography (PET) produces images reflecting physiologic of tissues. However for the photon attenuation, the spatial resolution of detectors and breathing related motions, these images have problem in achieving accurate lesion size and shape as they are typically noisy and blurry [6,7].

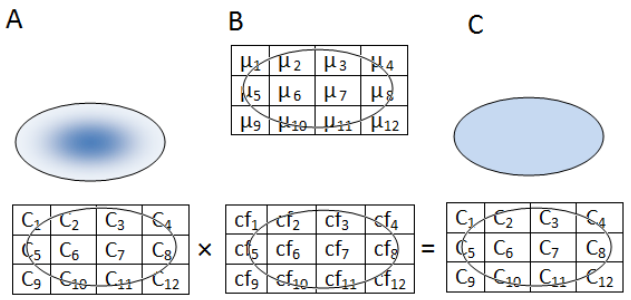

Figure 1: Concept of attenuation correction: Array of attenuation correction factors (B) can be determined from attenuation coefficient measurements determined from CT scan and used to correct emission counts from uncorrected PET scan (A) to provide final attenuation corrected PET scan.

Registration of PET and CT could lead to accurate differentiation of viable tumors from being masses, radiotherapy planning and monitoring treatment response and cancer staging [8].

Although a combined PET/CT automatically removes many of misalignments but breathing related non-rigid mismatches still persist during hybrid imaging. However, despite of advantages of CTAC in improving the accuracy of quantification in PET images, this method sometimes introduces an additional risk for artifacts on PET images specially when there is some level of misalignment between emission(PET) and transmission (CT) data.

Although there is a claim that the misalignment in PET/CT systems is minimum due to its hardware fusion concept but it should be emphasized that there is respiratory motion artifact in up to 96% of combined PET/CT examinations[8,4] in order to minimize the mismatch between CT and PET, developing of software-based image registration seems to be mandatory in order to increase the accuracy of CTAC.

In thorax and abdominal regions, the respiratory related motions are a major obstacle to handle and achieve satisfactory levels of registration reproducibility and accuracy.

Linear registration is not sufficient to cope with local deformation produced by respiration. Non-linear and non-rigid registration methods remain necessary to compensate and avoid for the vast cardiac and respiratory motions.

Non-rigid B-spline Free Form Deformation (FFD) technique is used to perform image registration. To motivate our choice of B-splines [9] as the most adequate basis functions among polynomials, wavelets and radial basis functions, to represent the deformation, some points should be considered. First it has small over lap, as a result makes faster algorithm and reduce the interdependency between the parameters.

Second, B-splines have the least number of contributing functions respect to polynomials, radial basis functions, and wavelets that makes it faster. B-spline On the other hand using FFD with support of local control provide us more accurate adaptive transformation to align the images. Non-rigid B-spline Free Form Deformation was chosen because

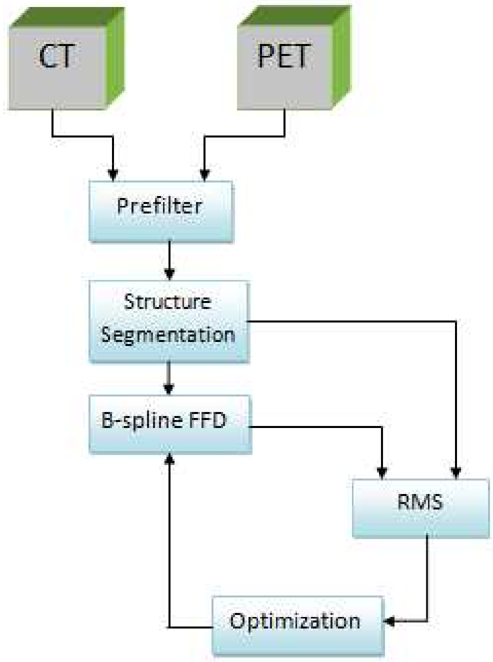

Figure 2: General scheme of the proposed approach

of the flexibility of FFD which comes from the fact that no assumptions on the underlying anatomy are made as its fastness in comparison with other elastic registration models such as fluid models.

The severer motions and the variability of the organs make unpractical to choose a more constrained model of the organs in thoracic oncology application. But special constraints must be added to convergence toward a proper registration [10]. In our proposed method an adaptive low pass filter followed by segmentation step are applied to identify corresponding structures in both modalities to provide us with the necessary initial constraint to guide the algorithm and prevent from getting trapped in local minima of the chosen similarity criterion.

II. METHODS AND MATERIAL

Twenty patients underwent oncological whole body imaging were used in this study. In general the images have matrix size of 512x512 and PET images have matrix size of 168x168.

A. *Initial Data Processing*

Before image registration, the CT images were resampled and the volume extents and pixel sizes were adjusted to equalize PET images. The choice of proper type of resampling technique between PET and CT depends on the trade-off between the desired accuracy of the interpolation and computational complexity.

B. *Image Segmentation*

In this step, first a low pass filter applied on the images in order to smooth the boundary of the lungs in both PET and CT images. This step gives us the initial constraints that will be used in FFD to import initial convergence and to increase the overall speed of the algorithm by reducing the complexity and defining initial condition of transformation.

The result of this step is shown in figure3: in which low pass filtering of CT and PET images produces, 2 pairs of images that are similar in view of boundaries and their differences is decreased to help us to make a good estimation of corresponded points as landmarks. This also makes the segmentation step to be done more easily. This step in addition to more correctly and consistently point pairs, leads to more accurate registration. In contrast to multi-resolution approach, this method helps us to facilitate the computation complexity while keeping the desired accuracy of registration, avoiding time consuming iterative steps like minimization algorithms. In the other word we filtered out all data but the main structures, then forwarded the output as an initial constraint or conditions to higher level (FFD) where more details will be considered.

In our approach after the segmentation step the Euclidian distance between some pairs of structures that belong to similar intensities but different structures like liver and kidney are defined in the whole body PET and CT image registration.

To segment the thoracic area in the PET images, adaptive thresholding based on the minimum and maximum intensity of each image is applied, where different intensity levels corresponds to different structures in the PET thoracic image. By applying this step, unwanted boundaries and structures are removed from the image providing much faster algorithm avoiding redundant calculations.

Once the step is done, we can easily define the candidate points or areas to become suitable landmarks. The output features of the segmentation process were applied to the PET and CT image. This information will plays an important role as constraints and conditions that should be meet in the FFD registration step. With this initialization, the search of final solution will be constrained, preventing from getting trapped in local minima of the chosen similarity criterion and were guided to convergence in a proper solution. So without low pass filtering, we encounter misregistration due to the lack of initial conditions.

C. B-spline FFD Registration

FFDs, originally introduced by [11] and was used for the first time for image registration by [12]. To the registration purposes, FFD is computed by means of linear combination of splines basis function as a particular case of non-linear transformation. In this technique deformation of the test image is achieved by tuning an underlying mesh of control points. As justified in section 1, B-spline based free form deformation has been chosen to cope with all possible deformations that may encounter in the mentioned application.

Once the FFD grid has been optimized, control points (CP) displacement are interpolated to obtain a smooth and continuous C^2 transformation [13].

A B-spline based FFD can be written as a 3D tensor product of one-dimensional cubic B-spline, producing a

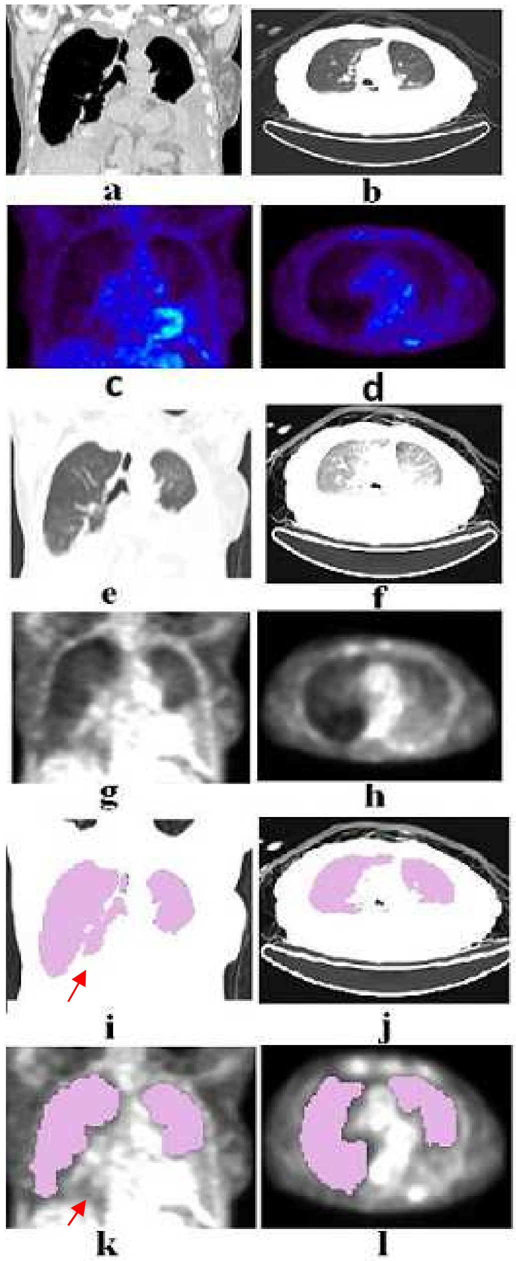

Figure 3: a Coronal b axial slice of original data volume (CT). c Coronal d axial slice of PET. e Low pass filtered coronal and f axial view of CT. g coronal and h axial slice of low pass filtered PET. i and j segmented CT ,coronal and axial. k segmented coronal pet, l segmented axial PET. Here (e-h) differences is decreased to make a good estimation of similar structure (lung) to use as an initial constraints (i-l) to guide FFD.

transformation separately for each axis. Let Φ denote an uniformly spaced grid of $n_x \times n_y \times n_z$ control points ϕ_{i+j+m} with spacing of δ where:

$$-1 \le i \le n_x - 1, -1 \le j \le n_y - 1, -1 \le k \le n_z - 1$$

Then the non-linear transformation for each image point x,y,z is computed as :

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

Here $i= [x/n_x] - 1$, $j= [y/n_y]-1$, and $k=[z/n_z]-1$, denote the index of the CP cell containing (x,y,z), and u, v and w are relative positions of (x,y,z) in the three dimensions. θ_0 through θ_3 are cubic B-splines.

$$\begin{aligned} \theta_0 &= (1-u)^3/6 \\ \theta_1 &= (3u^3 - 6u^2 + 4)/6 \\ \theta_2 &= (-3u^3 + 3u^2 + 3u + 1)/6 \\ \theta_3 &= u^3/6 \end{aligned} \quad (2)$$

Due to the compact support and separablity properties of B-spline they can be pre-calculated and stored in an array to accelerate the process. Moreover B-splines are scalable in the sense that any coarse level deformation can be represented at a finer scale without any loss of information [13].

D. Optimization

When the transformation model is chosen, the similarity criterion that will drive the optimization of CP displacements must be defined. As the labeled images with linear intensity relation are used, the Root Mean Square (RMS) difference of the corresponding pixel intensity, summed across the whole image, will be used in order to determine the optimal deformation parameters.

Optimization of the transformation parameters (for example control point displacement), is achieved by applying iteratively a gradient estimation to all control points simultaneously as proposed by [13] along the gradient direction until no further improvement of the similarity measure is found. At each iteration, finite difference local gradient estimation has computed for each control points. Furthermore a local spring force regularization term has been added to pull each nodes towards the centriod of its neighboring nodes to keep with the nodes from intersecting, which could lead to unwanted alteration of structure topology.

It should be point out that employing RMS as similarity criterion allows us to deal with several structures in each image at the same time to perform the registration.

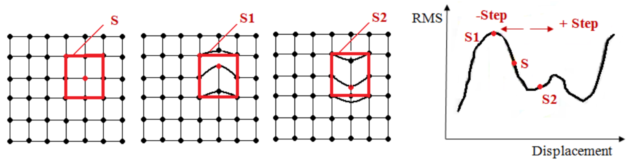

Figure 4: Gradient estimation based on local difference over the grid of control points.

III. RESULT

The desired accuracy of registration depends on several factors such as image modalities, spatial resolution or anatomical regions and nature of its deformation involved in the process. In this study , the required accuracy should be higher , due to the lack of identifiable structures in thoracic region and its severe deformation. The chosen accuracy must also assure a correct classification with respect to visualized tumors. Desired accuracy must have been chosen commensurate with the poorest spatial resolution, which is PET image resolution in our study.

In our application, visual inspection allows us to investigate the registration result for most important anatomical structures and control points.

For this purpose, several slices of both the original CT and registered PET images, as well as an overlay of chessboard image are presented. This representation was preferred to displaying a single overlay image because, in our opinion, this reduces measure subjectivity. Also Slices have been spaced through the volume in order to display the most significant thoracic structures. This is performed by means of an automatic procedure that uses CT segmented structures in order to decide which 2D slices must be chosen for evaluation purpose. However the user can choose any desired axial slices if they must be checked in order to confirm any evaluation score.

Figure 5 shows one pair of these 2D slices corresponding to axial (top) and coronal (bottom) slices with rulers, together with their corresponding overlay chessboard images.

It has to be point out that expert observers must use this visual inspection assessment, because emission PET contour structures are very difficult to localize, and it is easy to make mistake with other tissue different from the structure to validate.

Also we quantitatively evaluated the accuracy of the affine, free form deformation and its Constraint form. So we have computed Overlap Measure as a quantitative accuracy measure between reference and registered structure (lung). Overlap measure as a classical criterion, is equal to 1 if total overlap is obtained (best registration).

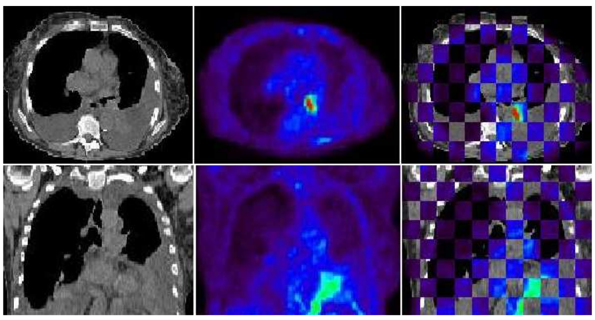

Figure 5: Example of 2D axial(top) and coronal (bottom) slice of the CT (left), registered PET (centre) volumes and the chessboard display (left). They are marked with the rulers that define landmark position where registration must be evaluated.

Figure 6 summarize the results which are obtained from the 5 data sets. As it is seen, affine is unable to give an acceptable result due to lack of its ability to handle the deformations, while applying the FFD improve the performance and helps to achieve an acceptable result. Maximum overlap measure in the best case for affine is 0.63 and by FFD is 0.76 while by means of our algorithm this amount is increased to 0.84. A clear improvement of the results (average 15%) achieved when the initial constraints superimposed to the FFD. This is due to the power of constrained FFD to converge to the best solution.

In addition to registration accuracy, performance time of the methods was analyzed. As expected the inclusion of the initial constraints allows us to speed up the overall process. The average computing time by simple FFD was around 3.5 hours. When constraining the FFD by means of prefiltering stage, considerably reduce the computational time over 35%.

The presented results prove that the proposed method can be used as a proper algorithm for image registration in thoracic region and potentially for other applications with sever deformation and motion artifacts.

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Our proposed algorithm by handling the local deformations specially in thoracic region, significantly reduces misregistration between PET and CT images lead to avoiding erroneous attenuation correction for PET reconstruction.

IV. CONCLUSION

Image registration is an important task that provides the ability of visual and diagnosis analysis of images acquired at different occasions by different modalities. We described a simple and fast registration algorithm that can cope with many deformation and severe breathing related motions in thoracic region based on B-spline free form deformation. The new idea of using low pass filtering before segmentation as an initialization procedure to take the necessary constraints has significantly speed up the convergence(35%) respect to simple FFD while increase the accuracy of registration almost 15% .

By the result have been achieved in our work we demonstrate that our proposed method can be a proper algorithm for data analysis in thoracic region and other applications with sever deformation and motions artifacts. The non-rigidity in the image and various local deformation is effectively modeled by means of B-spline based free form deformation which is clearly confirmed by the significant difference(0.15- 0.25) between affine and FFD overlaps.

The proposed method can be used for reducing the level of misregistration between CT and PET images before applying attenuation correction in order to reduce the CTAC artifacts arising from data mismatch. The method still need more validation and assessment in clinical environment and extensive phantom study.

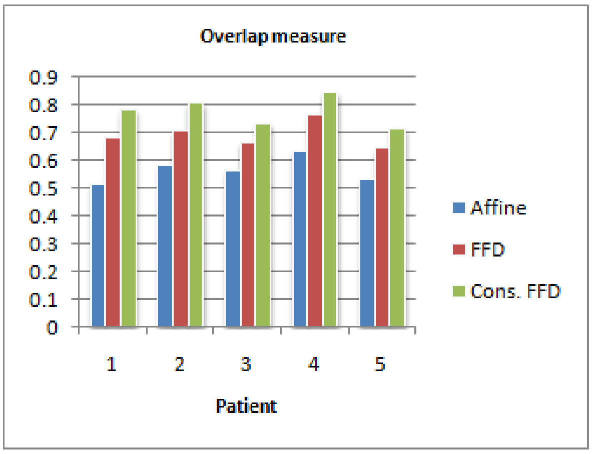

Figure 6: Measure of registration quality.

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