A Radiometry Tolerant Method for Direct 3D/2D Registration of Computed Tomography Data to X-ray Images

Transfer Function Independent Registration

Boris Peter Selby[1], Georgios Sakas[2], Stefan Walter[1], Wolfgang-Dieter Groch[3], Uwe Stilla[4]

[1]MedCom GmbH, Darmstadt
[2]Cognitive Computing and Medical Imaging, Fraunhofer IGD Darmstadt
[3]Fachbereich Informatik, University of Applied Sciences Darmstadt
[4]Photogrammetry and Remote Sensing, Technische Universitaet Muenchen
pselby@medcom-online.de

Abstract. As exact dose delivery is essential for radiological cancer treatment, image-guided radiotherapy (IGRT) methods are used to estimate corrections of the tumor alignment. This is often done through comparison of a computed tomography (CT) to the patient alignment visible in digital radiography images (DRs) acquired from within the treatment device. Digitally reconstructed radiography images (DRRs) computed from the CT are then geometrically registered to the DRs. A problem is that radiometric properties of DRs and DRRs can vary profoundly. If a registration algorithm does not use volumetric CT data directly it is unable to regard deviations of the physical image formation to the simulated image formation. We present a novel method allowing direct DR to CT registration. It is designed to be radiometry tolerant by adapting the simulated X-ray transfer function to observed DR intensities. This is done by solving an overdetermined system of equations given by the histograms along rays through the voxel matrix of the CT. Remaining errors serve as measure for the image dissimilarity, thus minimization in 6 degrees of freedom (DOF) gives the transformation between the images. Thereby higher radiometric tolerance can be achieved, as misalignments can be identified even if DR images are acquired with inappropriate radiation parameters.

1 Introduction and related Work

By registration of preoperative and intra operative data the misalignment of a radiation treatment target can be computed. Most approaches perform 2D-3D registration of CT to DR images by creating DRRs through projection of the CT and subsequent similarity maximization between DRRs and DRs [1, 2]. A problem is that radiometric properties of reconstructed DRRs often are totally different from the acquired DRs, as the physical image formation process can hardly be modeled due to complicated statistical properties of photon-matter interactions (i.e. photoelectric absorption, Rayleigh scattering, etc.) [3]. E.g. [4] and [5] among others propose Mutual Information (MI) as a robust similarity measure for multi-modal 2D-2D registration, but in the case of DR to CT registration MI is not able to incorporate 3D information from the CT and performance depends mainly on the implementation of the CT projection process. In [6] an approach is described that adapts CT data to the used X-ray energy to increase radiometric independency. Whilst this method is suitable for some cases, it is strongly limited as only a single free parameter (the X-ray kilovoltage peak) is adapted during ray-tracing, instead of regarding possible variations for each attenuation value. In this contribution a new Transfer Function Independent Registration (TFIR) approach is presented, reducing dependency of the 2D-3D registration from radiometric properties. The image formation is modeled and Least-Squares Fit is used to adapt it by comparison of DR intensities to rays through the CT. A similarity measure is derived from remaining errors between observed and simulated intensities. Results of our approach are compared to MI based registration.

2 Materials and Methods

Our approach employs the Least-Squares method, based on a functional model of the X-ray image formation process.

2.1 The TFIR Algorithm

In Fig. 1 we give an overview over the complete 3D-2D registration algorithm. Assuming a certain geometric alignment for the patient, modeled by the CT,

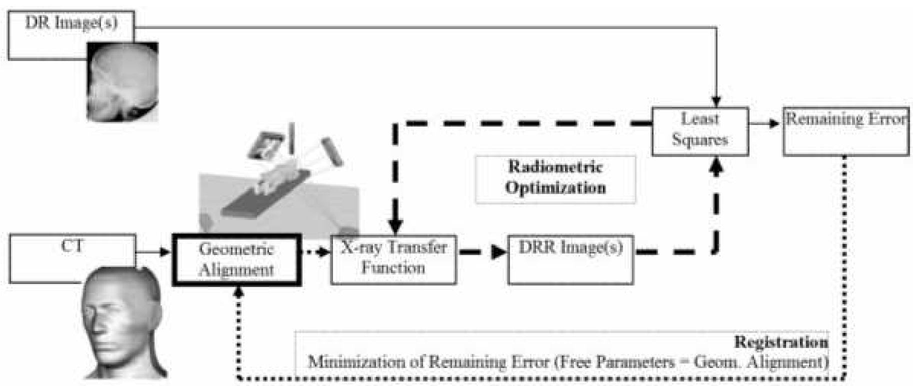


Fig. 1. The proposed 3D-2D registration algorithm, consisting of an optimization of the X-ray transfer function for image formation and the optimization of the geometric transformation in 6 DOF.

one or more DRR images are created (i.e. one per DR image), employing an X-ray transfer function, roughly emulating physical image formation. The resulting intensities are compared to the observed intensities from the DR(s). The transfer function is adapted using a constrained Least-Squares Fit. The calculation bases on an overdetermined linear system with high redundancy, and minimization of the remaining errors with the 6 parameters of rigid transformation of the patient leads to a corrected alignment.

2.2 Radiometric Optimization

First a simplified model of mono-energetic X-ray image formation based on the Lambert-Beer's Law is linearized. The photon fluence transmitted through a material is estimated by (1)

$$I_{tr} = I_0 * \exp\left(-\int_0^s \mu(\eta)d\eta\right) \tag{1}$$

where I_0 is the photon fluence that would be measured without any attenuation, s is the total length of the ray's path through matter and μ is the absorption coefficient at position η on the path. However, grey values G represent absorbed photons instead of transmitted photons in digital X-ray images so that $G = I_0 - I_{tr}$. We normalize pixel intensities G to a range between 0 and 1 and contribute to the fact that absorption values are represented in a discrete raster. Equation 2 then gives the grey value for a ray with N_s equal sized steps through the CT volume

$$G = 1 - \exp\left(-s * \sum_{i=1}^{N_s} \mu(i)\right) \tag{2}$$

Equation 3 shows linearized and simplified eq. 2 to obtain an observation b from a grey value G

$$b = \frac{-\ln(1-G)}{s} = \sum_{i=1}^{N_s} \mu(i) \tag{3}$$

Selected sets of pixels in the X-ray images are regarded as observations. According to the linearized model they are expressed as sums over the histograms of the respective rays through the CT. The equations for the observed intensities are

$$\begin{aligned} \hat{b}_1 = b_1 + \hat{r} &= \hat{x}_1 h_{11}\mu_1 + \hat{x}_2 h_{12}\mu_2 + \cdots + \hat{x}_u h_{1u}\mu_u = f_1(\hat{x}) \\ \hat{b}_2 = b_2 + \hat{r} &= \hat{x}_1 h_{21}\mu_1 + \hat{x}_2 h_{22}\mu_2 + \cdots + \hat{x}_u h_{2u}\mu_u = f_2(\hat{x}) \\ &\vdots \\ \hat{b}_n = b_n + \hat{r} &= \hat{x}_1 h_{n1}\mu_1 + \hat{x}_2 h_{n2}\mu_2 + \cdots + \hat{x}_u h_{nu}\mu_u = f_n(\hat{x}) \end{aligned} \tag{4}$$

where n corresponds to the number of observations b in the DR image (and corrected observations $\hat{b}$), $\hat{r}$ are the residuals, i.e. the observation errors, u equals the quantity of attenuation coefficients μ and h gives the occurrence of a certain attenuation coefficient on the respective ray through the CT (from the histograms of n different rays). $\hat{x}$ are unknown factors to the attenuation values.

We solve for factors $\hat{x}$ which modify the attenuations and adapt the CT transfer function to obtain observed intensities b. As negative values of $\hat{x}$ (negative attenuations) do not make physical sense, the solutions are constrained to $\hat{x} \geq 0$ with $i = 1 \ldots u$.

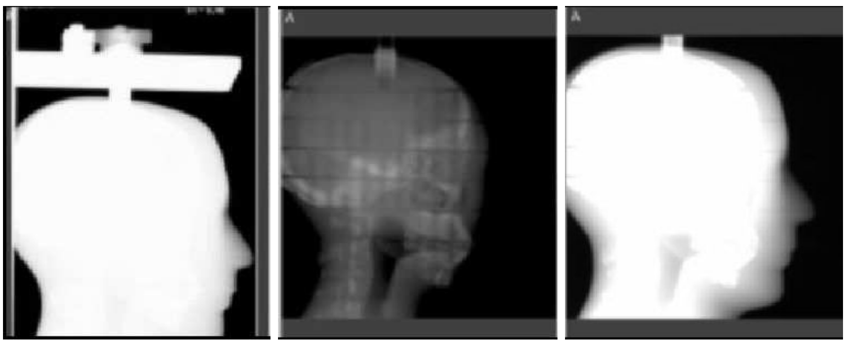
Non Negative Linear Least-Squares algorithm of Lawson & Hanson [7] and Singular Value Decomposition are used to solve for for the constrained $\hat{x}$.

2.3 Registration

Remaining errors $\hat{r}$ are computed by comparing the simulated intensities computed with optimized transfer function to observed DR intensities. Downhill simplex minimization of the root mean square (RMS) of residuals $\hat{r}$ gives the six transformations of the rigid registration of the CT to the X-ray image(s). In each step of the optimization process, the radiometric optimization is repeated and a new set of residuals is generated from (4).

3 Results & Discussion

Our approach was tested using different high resolution CT scans (2 anatomical phantoms of human heads and 1 human pelvis with approximately 1 mm voxel diagonal) and X-ray images acquired in a treatment machine. Image acquisitions with different X-ray tube settings were performed, including kilo-voltage peak settings ranging from 40 to 140 kVp and tube current settings ranging from 80 to 640 mA. In Fig. 2 an X-ray image with a low kVp setting is shown (a). In the center the DRR can be seen that was rendered with the initial X-ray transfer function. With respect to the X-ray image it varies profoundly in its radiometric



(a) X-ray image (b) Original DRR (c) Adapted DRR

Fig. 2. X-ray image of an anatomical head phantom acquired with the X-ray tube at 40 kVp, 100 mA and 100 ms (a); original DRR image (b); DRR image after several automatic adaptations of the attenuation coefficients during the registration process (c).

properties. In contrast, the DRR on the right, which was generated with the automatically adapted transfer function, looks similar to the DR.

Numerous comparisons of alignment computations using mutual information (MI) versus the proposed TFIR approach were performed. In most cases the target registration accuracy of TFIR was similar to the MI approach (approx. $\frac{1}{2}\cdot$DRR Resolution). Tests with DRs of low Signal to Noise Ratio and images containing features (e.g. head fixation device or metallic markers) not visible in the CT show that TFIR is more intolerant regarding those types of image degradation. Additionally, the computation time of TFIR is increased by approximately factor 8 with respect to the MI approach. Nevertheless, results also show that if the X-ray tube voltage is in a very high or low range, automatic transfer function optimization during registration can help to increase registration reliability. Providing higher tolerance against low kVp settings, the TFIR approach could allow reducing the dose delivered to the patient during the X-ray imaging in IGRT.

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