Improved Reconstruction of 4D MSCT Image Data and Motion Analysis of Lung Tumors Using Non-linear Registration Methods

H. Handels[1], R. Werner[1] T. Frenzel[2], D. Säring[1], W. Lu[3], D. Low[3], and J. Ehrhardt[1]

[1] Department of Medical Informatics, University Medical Center Hamburg-Eppendorf, Hamburg, Germany
[2]Hermann Holthusen Institute of Radiotherapy, AK St. Georg Hamburg, Hamburg, Germany
[3]Mallinckrodt Institute of Radiology, Washington University School of Medicine, St. Louis, USA

Abstract— In this paper, a non-linear registration method is used to interpolate and reconstruct (3D+t) CT data sets from multislice CT scans, which are collected simultaneously with digital spirometry. The non-linear registration approach applied is an optical flow based method. It estimates a velocity field between successive scans, which is used to reconstruct a 4D CT data set by interpolating data at user-defined tidal volumes. A qualitative and quantitative evaluation showed that artifacts can be reduced significantly by this technique. The comparison between slice changes inside a data segment and slice changes at segment borders enables a quantitative evaluation. For four patient data sets the artifacts could be reduced by 31.8 %, 29.9 %, 30.7% and 41.6% (mean over all data segments). Furthermore, the reconstructed 4D CT data sets are used for studying the motion of lung tumors and inner organs during the respiratory cycle. The reconstructed 4D data sets of 4 patients with lung tumors were used to quantify the individual tumor and organ movements during a breathing cycle. Based on the determined velocity field, trajectories of landmarks and surface points are analyzed. The motion of the lung tumor center in three orthogonal directions can be displayed and probabilities of lung tumor appearance are computed in 3D.

Keywords—**optical flow based interpolation, artifact reduction, motion analysis**

I. INTRODUCTION

Breathing motion is a significant error source of radiotherapy planning in the thorax region and the upper abdomen. For conventional conformal radiation therapy accounting for lung motion requires enlarging the safety margins. As a consequence the volume of irradiated healthy tissue is increased substantially. Therefore, a main challenge in radiotherapy is to take breathing motion into account by adapting the treatment according to this motion.

One approach is to use breath hold devices in order to immobilize the patient [1]. Via these techniques a significant reduction of target motion could be shown. This can also be achieved by respiratory gating [2]. Gating techniques do not directly compensate for breathing motion, so the radiation beam is switched off whenever the target is outside a predefined window. Often a combination of breath-hold techniques and respiratory gating is used. Such systems are currently in clinical use, for example deep inspiration breath hold [3] or active breath control [4]. Breath-holding techniques have the potential to reduce the effects of breathing motion [5,6], however, in practice they are limited by the fact that many patients cannot tolerate holding their breath. Furthermore, gating techniques are significantly increasing the expense of time for the patient and physician. Some attempts to explicitly account for free breathing motion are underway but suffer from little existing knowledge regarding the spatial-temporal behavior of anatomical and pathological structures involved. Tracking of the tumor motion is done by a combination of external infrared emitters on the patient's surface and implanted gold fiducials [6]. The position of the gold fiducials is computed repeatedly by x-ray imaging. Although first approaches exist to solve the technical problems arising from motion adaptive radiation therapy, an accurate non-invasive tracking method for following the tumor motion is still needed.

Spatio-temporal multislice CT (MSCT) data sets can be used to reconstruct 3D image data sets at different times [7]. The generated (3D+t) image data enables the measurement of movement of lung tumors and inner organs caused by breathing. Hence, these data sets open up the possibility to model the dynamic behavior of inner organs as well as to analyze respiratory lung tumor motion. The development of a model of free breathing motion and the identification of biometrical parameters that could be applied to radiotherapy planning is of high clinical relevance.

Because modern multislice CT scanners can only scan a limited region of the body simultaneously at different times, patients have to be scanned in segments consisting of multiple slices. For studying free breathing motion MSCT scans can be collected simultaneously with digital spirometry over several breathing cycles. The image data set is assembled by sorting the free breathing MSCT scans according to the couch position and the tidal volume. But artifacts can occur because there are no data segments for exactly the same tidal volume and all couch positions [8].

To reduce these artifacts an optical flow based reconstruction method was developed to generate interpolated data sets and to reconstruct 4D CT data at selected respiratory volumes. The reconstructed 4D CT data sets are used for studying tumor and inner organ motion during the respiratory cycle.

In this paper our non-linear registration approach for the improved and artifact reduced reconstruction of 4D CT data sets acquired during free breathing is presented. The optical flow based interpolation method used has been proven to be suitable to generate temporal images at user-defined times in high quality [9]. In the application considered the method was extended to reconstruct (3D+t) CT image sequences at user-defined respiratory volumes. The reconstructed 4D CT data sets are used for studying tumor and inner organ motion during the respiratory cycle.

II. METHODS

We used a multislice CT scanner operating in cine mode to acquire repeated scans per couch position over several free breathing cycles. Simultaneously the patient undergoes digital spirometry measurements. 15 scans were acquired at each couch position before the couch was moved to the adjacent position. This process was repeated until the entire thorax was scanned (16-19 couch positions) to associate the CT scans with tidal volumes. The patients were instructed to breath normally during the entire scanning sequence using the spirometer.

In a first approach the spirometry was used to generate a 4D image set by sorting free breathing multislice CT scans according to user defined tidal volume bins. For a given tidal volume a 3D CT data set was reconstructed by examining the spirometric record to determine which CT scan was acquired at a tidal volume closest to the desired volume at each couch position. This approach realizes a nearest neighbor interpolation of the segments. To prepare a (3D+t) data set, the 3D data sets for a scale of tidal volumes were arranged in series.

Free breathing causes the problem that there are no acquired data for exactly the user defined tidal volume. This induces artifacts similar to motion artifacts in 3D CT. This is especially noticeable when viewing sagittal reconstructions of the boundary between diaphragm and lung: the reconstructed diaphragm boundary shows an apparent and striking break-up (fig. 1, top). To avoid artifacts generated by missing CT scans for the desired volume an optical flow based reconstruction method was developed. In a first step, for each couch position the optical flow is determined between the two segments measured with tidal volume closest to the selected one. Here, a non-linear registration algorithm computes a velocity field describing the deformation of corresponding features.

The initial hypothesis of the optical flow based registration method used is that the pixel intensities of time varying image regions remain constant [10]. In the application considered, the image function depends on the tidal volume V instead of time. Therefore, the optical flow based approach is characterized by

$$\frac{dI(\boldsymbol{x}(V),V)}{dV}=0 \tag{1}$$

Hence, the velocity field $\boldsymbol{v}$ is given as:

$$\boldsymbol{v}=-grad(I)\frac{\partial_V I}{\left\|grad(I)\right\|^2}\ , \tag{2}$$

where $grad(I)$ is the spatial image gradient. However, equation 2 is ill-posed and only the motion component in direction of the local brightness gradient of the image intensity function may be estimated [10]. As a consequence, the flow velocity cannot be computed locally without introducing additional constraints. In our implementation the necessary regularization is done by Gaussian smoothing of the velocity field. Hence, the velocity field is computed by an iterative algorithm similar to the demons-based registration method [11].

Furthermore, problems occur near segment borders. This is caused by voxels that do not have corresponding voxels in the considered couch position, as some structures may change from one data segment into another segment during the respiratory cycle. To overcome this CT scans at adjacent couch positions are also taken into account for the registration process.

Based on the estimated velocity field $\boldsymbol{v}$ corresponding voxels are defined in the two initial images. The interpolated image values are computed as weighted average of the gray values of corresponding voxels. This technique is applied to overcome the problem that the intensity conversation assumption might not be fulfilled and that structures are only contained in one of the interpolated images.

The resulting (3D+t) CT data set is used to analyze the respiratory motion. In a first step, the lung, the skin and the bronchial tree are segmented for any reconstructed tidal volume using region growing techniques and interactive correction. Surface models of the segmented organs are generated in order to enable the visualization of the 4D breathing motion. Anatomical landmarks, e.g. the branches of the bronchial tree, are determined interactively and the trajectories of the selected points are analyzed and visualized.

Furthermore, the segmented 4D data sets are used to calculate the optical flow of the organ surfaces. Therefore, a non-linear registration similar to the algorithm described in [11] is performed. The resulting velocity fields are used to approximate the trajectories of points on the organ surface. Hence, the maximum displacement of any surface point can be calculated and regions with large respiratory motion are identified. Additionally, the trajectory of the mass center of the lung tumor can be computed, and its motion in different directions can be analyzed.

III. Results

Four tumor patients were examined with a 12 slice MSCT scanner. 16-19 segments, each consisting of those 12 slices, were scanned at 15 different times of the breathing cycle. The position within the breathing cycle was measured using a digital spirometer. (3D +t) CT data sets were reconstructed by sorting the segments according to the tidal volumes and by optical flow based interpolation.

The first reconstruction method generates artifacts at the edges of neighboring segments that were not scanned exactly at the same period of the breathing cycle (fig. 1, top). With the optical flow based interpolation method described above the artifacts are reduced significantly (fig. 1, bottom).

The comparison between slice changes inside a data segment and slice changes at segment borders enables a quantitative evaluation. For the four patient data sets the artifacts could be reduced by 31.8 %, 29.9 %, 30.7% and 41.6% (mean over all data segments).

3D image data sets are computed at volumes corresponding to equidistant times, and the lung tumor is segmented at each time step. Hence, probabilities of lung tumor appearance can be computed in 3D. The estimated appearance probabilities visualize the movement of the tumor during the respiratory cycle in one static image (fig. 2).

The reconstructed 4D data sets are used to quantify organ displacements and to visualize the thoracic organ motion (fig. 3).

Based on the velocity field determined, trajectories of landmarks and surface points are analyzed. The motion of the tumor during breathing is described by the 3D trajectory of its mass center. The motion of the tumor's mass center at different time frames can be displayed by the projection of the trajectory in craniocaudal, (CC), anteroposterior (AP) and lateral (LA) direction (fig. 4).

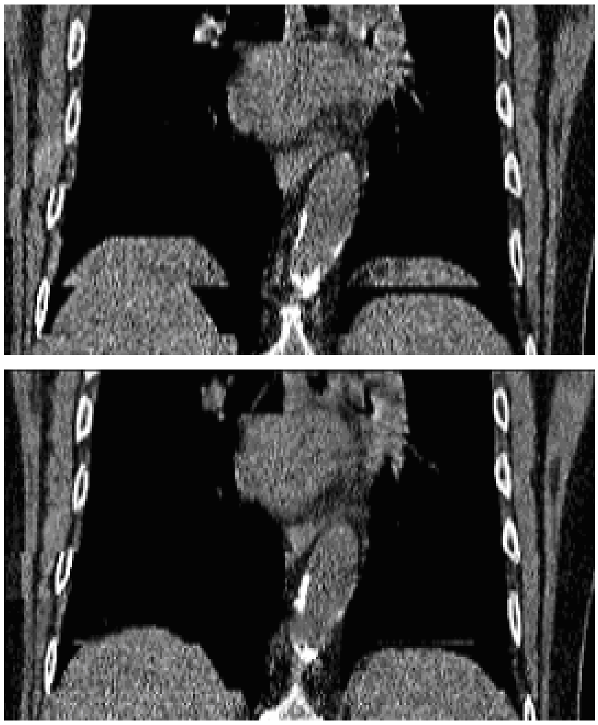

Fig. 1: Artifacts at the diaphragm with the nearest neighbor method for the reconstruction of 4D CT data (top) and improved optical flow based reconstruction (buttom)

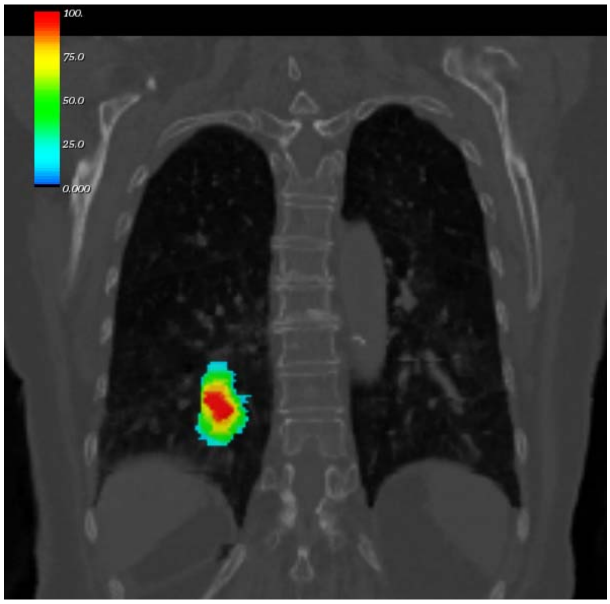

Fig. 2: Color-coded appearance probabilities of a tumor

Fig. 3: Gray-value coded visualization of the maximum distances between corresponding points during the breathing cycle.

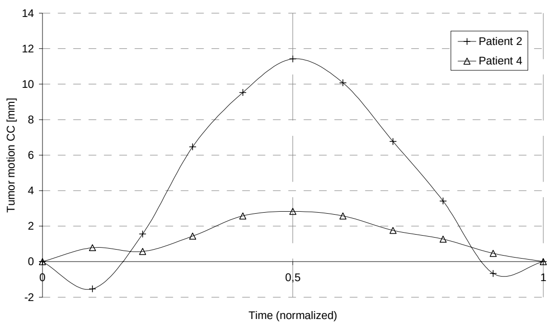

Fig. 4: Motion of the tumors of two patients in craniocaudal (CC) direction.

IV. Conclusion

The optical flow based registration method presented improves the image quality of reconstructed 4D CT data sets at user-defined tidal volumes, significantly. The reconstructed 4D image data sets are used to model and analyze the influence of respiratory motion on motion of lung tumors. The results presented are based on the analysis of four patient data sets. The appearance probability distribution changes from patient to patient depending on the localization of the tumors in the lung and the individual differences in their breathing motion. In further research the number of patient data sets with lung tumors will be increased and correlations between the respiratory state and the motion of skin markers will be investigated in order to predict the abdominal organ motion from external, non-invasive tracking data. Furthermore, it will be of interest to analyze the breathing behavior of different patients in more detail in order to identify typical breathing patterns.

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Address of the corresponding author:

Author: Heinz Handels
Institute: Department of Medical Informatics
University Medical Center Hamburg-Eppendorf
Street: Martinistr. 52
City: D- 20246 Hamburg
Country: Germany
Email: h.handels@uke.uni-hamburg.de