# Model-based Risk Assessment for Motion Effects in 3D Radiotherapy of Lung Tumors

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# ABSTRACT

Although 4D CT imaging becomes available in an increasing number of radiotherapy facilities, 3D imaging and planning is still standard in current clinical practice. In particular for lung tumors, respiratory motion is a known source of uncertainty and should be accounted for during radiotherapy planning – which is difficult by using only a 3D planning CT. In this contribution, we propose applying a statistical lung motion model to predict patients' motion patterns and to estimate dosimetric motion effects in lung tumor radiotherapy if only 3D images are available. Being generated based on 4D CT images of patients with unimpaired lung motion, the model tends to overestimate lung tumor motion. It therefore promises conservative risk assessment regarding tumor dose coverage. This is exemplarily evaluated using treatment plans of lung tumor patients with different tumor motion patterns and for two treatment modalities (conventional 3D conformal radiotherapy and step-& shoot intensity modulated radiotherapy). For the test cases, 4D CT images are available. Thus, also a standard registration-based 4D dose calculation is performed, which serves as reference to judge plausibility of the model-based 4D dose calculation. It will be shown that, if combined with an additional simple patient-specific breathing surrogate measurement (here: spirometry), the model-based dose calculation provides reasonable risk assessment of respiratory motion effects.

Keywords: motion estimation, registration, modeling, radiotherapy

## 1. PURPOSE

Although 4D(=3D+t) CT imaging is becoming increasingly important in radiotherapy of thoracic and abdominal tumors (at least in the US and other industrialized countries), 3D CT is still the basis for treatment planning in the majority of medical facilities.<sup>1</sup> However, motion amplitudes of especially lung tumors can be up to three or more centimeters even during regular breathing.<sup>2</sup> By 3D CT-based radiotherapy treatment planning, exact patient-specific tumor motion patterns and amplitudes are not known by definition and treatment margins are dimensioned (more or less) empirically. As treatment planning is always a tradeoff between increasing safety margins to ensure dose coverage of the tumor and decreasing them to spare normal tissue, even a relatively vague risk assessment (in the sense of "What would be the dosimetric/outcome consequences of under-/oversizing the margins?") could provide valuable information for radiotherapists and lung tumor treatment – especially in the absence of temporally resolved planning data.

Based on the assumption that in principle the physiology of breathing should be similar for different individuals, we recently presented an approach for generation of a mean lung motion model (4D-MMM = 4D Mean Motion Model) based on a collective of thoracic 4D CT image sequences.<sup>3</sup> In this contribution we propose applying the 4D-MMM for estimation of the (dosimetric) impact of respiratory motion in 3D radiotherapy planning of lung tumors. Currently, the 4D-MMM represents the mean lung motion in data sets unaffected by lung pathologies. Aiming at lung tumor motion prediction, the model motion patterns have been shown to be representative for small lung tumors not attached e.g. to the chest wall or the mediastinum; otherwise the model tends to overestimate tumor motion. This, in turn, means that lung tumors which are adherent to non-lung structures or larger in size hinder (at least local) lung dynamics.<sup>4</sup> This interpretation is in wide agreement with the findings of Plathow *et al.* and Liu *et al.* who analyzed lung tumor motion patterns in extensive patient collectives.<sup>5, 6</sup> They demonstrated that larger tumors exhibit less motion than smaller ones (even for similar positions inside the lung) and that motion is more pronounced in the contralateral lung than in the ipsilateral lung containing

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lesions. While this can be seen as a drawback in modeling and the 4D-MMM construction itself, we consider this to be advantageous in the case of assessing dosimetric motion effects: Regarding clinically relevant tumor dose coverage the effects will be overestimated if using the 4D-MMM for estimation of the patient's tumor motion. The model-based assessment therefore represents a risk assessment in the sense of a worst-case scenario.

When adapting the 4D-MMM to a particular patient, the mean motion model can be used directly to transfer motion patterns representing the mean depth of breathing in the patient collective underlying model generation. This, of course, is only a rough approximation of patient-specific breathing patterns. To become closer to the patient's individual lung motion patterns, we further suggested measuring a (simple) breathing signal (e.g. spirometry or bellows belts) and scaling the model depth of breathing according to the measurements during adaptation of the 4D-MMM. Here, we analyze both approaches: We first assume that (in agreement with 3D radiotherapy planning practice) only a 3D CT image is available for planning. Consequently, in a first run the unscaled model is adapted to the patients' anatomy to assess motion effects on the (statically planned) dose distribution. Intending to achieve a more precise motion estimation, we then scale the model depending on patient-specific spirometry measurements and again analyze dosimetric motion effects. However, for all patients 4D CT data sets are available. Thus, based on motion field estimation by registration of the 3D CT frames of the 4D CT image sequences we also perform a standard 4D dose calculation by dose accumulation for each patient. The resulting dose distribution serves as comparison case to judge plausibility of the model-based estimation of dosimetric motion effects and model-based 4D dose calculation, respectively.

## 2. METHODS

The proposed workflow for model-based risk assessment basically consists of four steps: generation of the 4D-MMM, adapting the 4D-MMM to the planning 3D CT of the patient to be considered (plus incorporating additional patient-specific motion information if they are available), estimating patient-specific 4D dose distributions (= dose accumulation) using a precomputed 3D treatment plan and the motion information provided by the 4D-MMM, and finally evaluating resulting dosimetric measures/motion effects. Both the 4D-MMM generation and a dose accumulation in general are based on image registration. This section therefore starts with a brief description of the registration approach applied in this study (Sec. 2.1). The principles of the model generation and adaptation process and dose accumulation are then explained in Sec. 2.2 to 2.4. To keep the single methodical sections as compact and comprehensible as possible, we will not go into too many technical details. Instead, the interested reader will be referred to related publications for further information on the topics covered.

## 2.1 Diffeomorphic registration for motion estimation and atlas-patient matching

Comprising the tasks of intra-patient registration in 4D CT image sequences (to assess breathing motion information for individual subjects) and interpatient or patient-atlas matching (to establish a common coordinate system for all patients; cf. the following section), we apply a diffeomorphic non-linear intensity-based non-parametric registration scheme as described in detail in Schmidt-Richberg *et al.*<sup>7</sup> As part of a multi-institutional study on thoracic image registration the accuracy of our registration implementation has been proven to be in the order of voxel size when applied for intrapatient registration of thoracic CT images.<sup>8</sup>

Implemented within a classical variational registration approach ( $\mathcal{D}$ : distance measure,  $\mathcal{S}$ : smoothness or regularization term.  $\alpha$ : weighting coefficient), i.e.

$$\mathcal{J}[\varphi] = \mathcal{D}[I_{\text{ref}}, I_{\text{tar}} \circ \varphi] + \alpha \mathcal{S}[\varphi] \xrightarrow{\varphi} \min, \qquad (1)$$

the basic idea is to search for a transformation  $\varphi : \Omega \to \Omega$  that minimizes a normalized variant of the sum of squared intensity differences between a reference image  $I_{\text{ref}}$  and the transformed target image  $I_{\text{tar}} \circ \varphi$  $(I_{\text{ref}}, I_{\text{tar}} : \Omega \to \mathbb{R})$ . To prevent ill-posedness of the minimization problem, a diffusion regularization approach is adopted. Aiming at diffeomorphic transformations and exploiting the Lie group-like structure of the group of diffeomorphisms on  $\Omega$  (see e.g. Arsigny *et al.*<sup>9</sup> for the mathematical background) the sought transformation is parameterized by a velocity field  $v : \Omega \to \mathbb{R}^3$ , i.e.

$$\varphi = \exp\left(v\right).\tag{2}$$

The exponentiation map ensures  $\varphi$  to be diffeomorphic if the velocity field is sufficiently smooth (note that v is a standard, not necessarily diffeomorphic transformations on  $\Omega$ ).<sup>10</sup> Here, to guarantee smoothness, the regularizer S of Eq. 1 acts directly on v.

Besides restricting resulting transformations to being diffeomorphisms, which itself can be considered a "natural choice in the study of anatomy as [...] smoothness of anatomical features [...] is preserved, and coordinates are transformed consistently",<sup>11</sup> the chosen registration approach additionally features an efficient computation of inverse transformations via  $\varphi^{-1} = (\exp(v))^{-1} = \exp(-v)$ . This property will later be advantageous especially in the context of the 4D-MMM generation and model adaption to a patient.

#### 2.2 Generation of the mean lung motion model

The model generation process applied in this study is explained in detail in Ehrhardt  $et \ al.^3$  where we would like to refer to for further information; the basic idea can be summarized as follows:

Given a collective of 4D image sequences of different patients, the generation of the mean lung motion model consists of four steps. At the beginning, subject-specific motion fields are estimated in the 4D image sequences of the different patients by non-linear registration with respect to a common reference breathing phase (here: using the diffeomorphic registration as described above). Thus, let  $(I_{p,j})_{j \in \{1,...,n_{Ph}\}}$  denote the image sequence of patient  $p \in \{1, \ldots, n_{Pat}\}$  with j representing the different breathing phases. We further assume that for the different patients the breathing phases correspond to each other; consequently, no temporal alignment of the sequences is required. Then, the first modeling step yields a series of transformation sequences  $(\Phi_p)_{p \in \{1,...,n_{Pat}\}}$ with  $\Phi_p = (\varphi_{p,j})_{j \in \{1,...,n_{Ph}\}}$  being the transformations to match  $I_{p,j}$  and the reference image  $I_{p,ref}$ .

In the second step, a 3D average shape and intensity model, also called lung atlas, is generated from the reference images  $I_{p,ref}$  of the different patients. To provide a bias-free atlas we adopt an atlas generation technique proposed by Guimond *et al.*<sup>12</sup> The reference image of a randomly selected patient is chosen as an initial atlas. The reference images of the other patients are then registered to the initial atlas (affine pre-registration, followed by a non-linear diffeomorphic registration) and transformed to fit the atlas coordinate system. Within the atlas coordinate system the intensities of the transformed CT images are averaged, resulting in a mean intensity image. Finally, an average patient-atlas transformation is computed and its inverse applied to the mean intensity image. The result defines a new atlas (in the sense of a mean intensity and shape image), and the former steps are iterated until convergence.

In detail, we use the Log-Euclidean framework for computing the average transformations to ensure resulting patient-to-atlas transformations

$$\psi_p = \exp\left(w_p\right) \colon \Omega_p \to \Omega_A,\tag{3}$$

being diffeomorphic (please note that in our case  $\Omega_p = \Omega_A$ ; the differentiation between patient and atlas coordinate system is made to facilitate understandability of subsequent explanations). This step finally results in a mean intensity and shape image  $\bar{I}_{ref} : \Omega_A \to \mathbb{R}$  and a series of transformations,  $(\psi_p)_{p \in \{1,...,n_{Pat}\}}$ , mapping the patient-specific reference images  $I_{p,ref}$  to the atlas coordinate system.

In the third step, the generated average shape and intensity model is used as anatomical reference frame to match the estimated subject-specific motion fields  $\varphi_{p,j}$  to the atlas coordinate system. This is accomplished by

$$\tilde{\varphi}_{p,j} = \psi_p \circ \varphi_{p,j} \circ \psi_p^{-1} = \exp\left(w_p\right) \circ \exp\left(v_{p,j}\right) \circ \exp\left(-w_p\right),\tag{4}$$

and analogously for the velocity fields. Thus, this step yields a series of patient-specific transformation sequences  $(\tilde{\varphi}_{p,j})_{j\in\{1,\ldots,n_{\text{Ph}}\}}$  and corresponding velocity fields, but defined in the atlas coordinate system (i.e.  $\tilde{\varphi}: \Omega_A \to \Omega_A$ ).

In the fourth and final step, these transformations are averaged by

$$\bar{\varphi}_j = \exp\left(\bar{v}_j\right) = \exp\left(\frac{1}{n_{\text{pat}}} \sum_{p=1}^{n_{\text{pat}}} \tilde{v}_{p,j}\right),\tag{5}$$

resulting in a series of mean transformations  $(\bar{\varphi}_j)_{j \in \{1,...,n_{\text{Ph}}\}}$ . Together,  $(\bar{\varphi}_j)_{j \in \{1,...,n_{\text{Ph}}\}}$  and the mean shape and intensity image  $\bar{I}_{\text{ref}}$  define a mean lung motion model 4D-MMM.

# 2.3 Adaptation of the mean lung motion model for patient-specific motion estimation

For adaptation of the 4D-MMM to predict lung motion of a patient s, the average mean and intensity image  $\bar{I}_{\text{ref}}$  is first registered to the patient's 3D CT  $I_s$ . Thereby, we assume the breathing phase of the patient's CT  $I_s$  to be corresponding to the reference phase chosen for the 4D-MMM generation. The resulting transformation  $\psi_s : \Omega_s \to \Omega_A$  is used to transfer the motion information from the atlas to the patient coordinate system. Similar to Eq. 4, this can be done using directly the mean motion fields of the 4D-MMM. Then, the predicted motion between the reference breathing phase and another phase j would be given by

$$\hat{\varphi}_{s,j} = \psi_s^{-1} \circ \bar{\varphi}_j \circ \psi_s. \tag{6}$$

However, by only accounting for the mean motion of the patient collective the potential occurence and consequences of interpatient differences in the depth of breathing are neglected. Thus, in this article we propose to scale the mean fields wrt. additional patient-specific measurements, i.e. we use

$$\hat{\varphi}_{s,j}^{\lambda} = \psi_s^{-1} \circ \bar{\varphi}_j^{\lambda} \circ \psi_s = \psi_s^{-1} \circ \exp\left(\lambda \bar{v}_j\right) \circ \psi_s \tag{7}$$

instead of Eq. 6 for prediction purposes.

As a proof of concept, in this study we will use spirometry measurements for dimensioning the scaling parameter  $\lambda$ . This will be detailed in Sec. 3.

#### 2.4 Radiotherapy treatment planning and principles of dose accumulation

In this contribution we consider two radiotherapy treatment planning modalities: Conventional 3D conformal radiotherapy (3D CRT) and step-&-shoot intensity modulated radiotherapy (IMRT). 3D plans are created with a prescribed dose to the tumor of 50 Gy (fractionation:  $25 \times 2$  Gy) and standard safety margins (approximately 10 mm isotropic margin between the gross tumor volume [GTV] and the planning target volume [PTV]).

To analyze the impact of respiratory motion on the (planned) dose distributions, i.e. to estimate the dose which will actually be delivered to the patient for a given treatment plan and incorporating knowledge about breathing motion, the technique of dose accumulation (also called 4D dose calculation) is employed. This means that estimated motion fields are applied to track the voxels of the reference frame over the breathing cycle and the dose received by the voxels at the different breathing phases is accumulated. Mathematically formulated, we compute a dose  $D^{4D}: \Omega \to \mathbb{R}_+$  by integrating the dose rate  $\dot{D}: \Omega \times \mathbb{R} \to \mathbb{R}_+$  over the time of treatment T,

$$D^{\rm 4D}(x) = \int_{T} \dot{D}(x(t), t) \, dt = \sum_{k=1}^{n_{\rm Fields}} \int_{T_k} \dot{D}(x(t), t) \, dt.$$
(8)

Thereby, the voxel trajectory over a breathing cycle is usually approximated by  $x(t) = (\varphi_1(x), \ldots, \varphi_{n_{\text{Ph}}}(x))^T$  with the fields  $\varphi_j$  resulting from registration of the frames of a patient-specific 4D CT image sequence to the planning CT frame. The summation in the last part of Eq. 8 further accounts for the fact that a radiotherapy treatment plan usually comprises different irradiation angles and irradiation fields, respectively. In the case of IMRT, the single fields additionally consist of a number of so-called subfields or segments of potentially short irradiation times. The additional segmentation of the fields finally results in slightly different accumulation after temporal discretization of Eq. 8, which will be explained below.

However, following Eq. 8 it can be seen that the principle of model-based 4D dose calculation (i.e. using the 4D-MMM) and 4D dose calculation by means of patient-specific 4D CT data are similar; one basically replaces the fields  $\varphi_j$  by the model-based predictions  $\hat{\varphi}_j$  and  $\hat{\varphi}_j^{\lambda}$ , respectively. Differences occur only in detail: Based on patient-specific 4D CT images in standard dose accumulation 3D dose distributions corresponding to the original 3D treatment plan are calculated for all breathing phases and further used to approximate the continuously defined dose rate. Thereby, one accounts for density variations in the lungs due to breathing. For model-based dose calculations, we do not recalculate static dose distributions for any other than the planning phase as we assume the planning 3D CT to be the only image available.



Figure 1. Principle of dimensioning the factor  $\lambda$  used for scaling the 4D-MMM mean motion fields when adapting the fields for subject-specific motion prediction: For the patient's spirometry records the maximum peaks of the individual breathing cycles are determined and sorted into a histogram [Figure (a)]. A Gaussian function is then fitted to the distribution of the volumes [Figure (b)]. We finally aim to capture the change of air content of the patient's lungs which corresponds to the mean plus one standard deviation of the Gaussian function when applying the scaled 4D-MMM mean motion field between the reference phase and end-inspiration to the patient's reference CT. For comparison purposes, the tidal volume corresponding to the application of the unscaled 4D-MMM is also indicated as part of the figures.

#### 2.4.1 Conventional 3D conformal radiotherapy

For conventional 3D conformal radiotherapy, the irradiation times for single treatment fields can be assumed to be long in comparison to the patient's breathing period. In this case, discretization of Eq. 8 yields a quite simple formula for calculation of the 4D dose to a voxel  $x \in \Omega$ , given by

$$D^{\text{4D,CRT}}\left(x\right) := \frac{1}{n_{\text{Ph}}} \sum_{j=1}^{n_{\text{Ph}}} D_j\left(\varphi_j\left(x\right)\right) \tag{9}$$

(see e.g. Werner *et al.*<sup>13</sup> for more information on the derivation).  $D_j$  denotes the dose for the 3D treatment plan, but computed for the patient's CT at breathing phase j ( $\forall j : D_j = D_{ref}$  for model-based dose calculation).  $\varphi_j$  is the motion field estimation between the planning/reference phase and j (to be replaced by  $\hat{\varphi}_j$  and  $\hat{\varphi}_j^{\lambda}$  for 4D-MMM-based dose accumulation).

#### 2.4.2 3D (step-&-shoot) intensity modulated radiotherapy

The situation becomes more complicated for IMRT because segment irradiation times can be shorter than the breathing cycle. Thus, the 4D dose has to be calculated using segment-specific weighting coefficients, i.e.

$$D^{\text{4D,IMRT}}\left(x\right) := \sum_{k=1}^{n_{\text{Fields}}} \sum_{j=1}^{n_{\text{Fh}}} \alpha_{k,j} D_{k,j}\left(\varphi_{j}\left(x\right)\right).$$
(10)

k denotes the individual IMRT segments and  $D_{k,j}$  the dose distribution yielded by delivery of the k-th segment at breathing phase j. The specific value of a coefficient  $\alpha_{k,j}$  depends on factors such as the segment irradiation length and the breathing phase at the beginning of its delivery; for details on the dimensioning of the coefficients for step-&-shoot IMRT please refer again to Werner *et al.*<sup>13</sup>

## **3. RESULTS**

To demonstrate feasibility of model-based dose accumulation and evaluate suitability of the 4D-MMM for risk assessment in 3D radiotherapy, we proceed as follows: Based on 3D CRT and 3D step-&-shoot IMRT treatment plans for three lung tumor patients with significant tumor motion amplitudes (i.e. tumor motion magnitude >5m; cf. Keall *et al.*<sup>2</sup>) we perform 4D dose calculations as described in the methods section by (a) using the

			Conv. 3D conformal radiotherapy		Intensity modulated radiotherapy	
	Tumor motion	Motion field	min./max. CTV dose	max. CTV dose differences to plan	min./max. CTV dose	max. CTV dose differences to plan
#1	12.2  mm	$\varphi$	94.2 / 103.0%	6.3%	93.1 / 111.4%	8.9%
		$\hat{\varphi}$	88.3 / 103.4%	12.1%	92.5 / 110.7%	11.6%
		$\hat{\varphi}^{\lambda=1.1}$	84.8 / 103.0%	15.6%	$91.7 \ / \ 110.6\%$	14.1%
#2	$6.7 \mathrm{mm}$	$\varphi$	$98.6 \ / \ 105.6\%$	1.3%	$94.7 \ / \ 108.2\%$	3.5%
		$\hat{arphi}$	$98.4 \ / \ 105.8\%$	2.9%	$94.5 \ / \ 106.4\%$	4.3%
		$\hat{\varphi}^{\lambda=1.15}$	97.8 / 105.7\%	3.5%	94.1 / 106.1\%	4.9%
#3	$19.6~\mathrm{mm}$	$\varphi$	$92.3 \ / \ 102.0\%$	7.4%	$90.8 \ / \ 112.3\%$	11.7%
		$\hat{arphi}$	$96.2 \ / \ 103.9\%$	4.7%	91.6 / 110.9%	13.6%
		$\hat{\varphi}^{\lambda=1.25}$	93.3~/~103.8%	7.5%	$89.2 \ / \ 109.1\%$	16.1%

Table 1. Dosimetric quantities for evaluation of motion-induced effects inside the clinical target volume CTV, given in percentage of the prescribed single fraction dose. For IMRT dose accumulation the values depend on parameters such as the breathing phase at the beginning of the irradiation delivery; the entries listed here correspond to the worst case scenarios considered.<sup>13</sup>

patient-specific 4D CT data set and registration-based motion-field estimation therein [serves as ground truth for evaluation], (b) applying the unscaled mean motion field of the 4D-MMM for prediction of the patient's motion patterns, and (c) by adapting the 4D-MMM by means of patient-specific spirometry measurements. The data collective for generation of the 4D-MMM consists of 12 4D CT data sets of patients without obvious impairment of breathing physiology. The three lung tumor patients acting as test cases are not part of the model training set. Due to computational efforts we restrict the breathing phases modeled to end-inhalation (EI), end-exhalation (EE), mid-inhalation (MI), and mid-exhalation (ME); end-inhalation serves as reference breathing phase.

As written in Sec. 2.3, in this study we propose to dimension the factor  $\lambda$  for scaling the 4D-MMM mean motion fields by analyzing spirometry records of the patients' breathing. In our case, they were acquired during the 4D CT image acquisition for retrospective image reconstruction.<sup>14–16</sup> The principle of dimensioning  $\lambda$  is illustrated in Fig. 1. For each patient, we identify the maximum peaks of the record and fit a Gaussian function to the distribution of corresponding spirometry volumes. The spirometry-measured volume is proportional to the change of the air content of the patient's lungs, with a constant of proportionality of 1.11 that can be explained by the ideal gas law.<sup>16,17</sup> Now, let  $\mu_{s,\text{spiro}}$  and  $\sigma_{s,\text{spiro}}$  denote the mean and the standard deviation of the Gaussian fit for subject s and  $\Delta V_{s,\text{air}} = 1.11 \cdot (\mu_{s,\text{spiro}} + \sigma_{s,\text{spiro}})$  a respective change in the lungs air content. Then, we determine the sought scaling factor  $\lambda$  by

$$\left| \left( V_{s,\text{air}} \left( I_{s,\text{EI}} \right) - V_{s,\text{air}} \left( I_{s,\text{EI}} \circ \hat{\varphi}_{s,\text{EE}}^{\lambda} \right) \right) - \Delta V_{\text{air}} \right| \xrightarrow{\lambda} \min.$$
(11)

For details on the computation of the air content  $V_{s,air}$  in CT images please again refer to Ehrhardt *et al.*<sup>3</sup> For the three patients of this study,  $\lambda$  was between 1.10 and 1.25 (see also Table 1).

Examples of the planned 3D dose and the accumulated dose distributions resulting from patient-specific motion field estimation by registering the CT frames of the patient's 4D CT image and estimated by application of the scaled mean 4D-MMM fields are shown in Fig. 2 (data: patient 1; treatment modality: 3D-CRT); it becomes obvious that the accumulated dose distributions look very similar. Additionally, differences between the planned and the accumulated dose distributions are shown in Fig. 2. The figure confirms the hypothesis underlying this contribution: At least for the patient considered, the 4D-MMM-based overestimates the dosimetric motion effects; it therefore presents a conservative risk assessment.

For further quantitative evaluation purposes we concentrated on motion effects on dosimetric quantities for the clinical target volume (CTV; i.e. tumorous tissue to receive within 95% and 107% of the prescribed dose according to international guidelines<sup>18</sup>). We considered the 95%- and 107%-doses with regard to the work-flow of 3D radiotherapy planning: If CTV voxels are observed which receive (according to the 4D dose estimation)



Figure 2. Illustration of model-based risk assessment for motion effects in 3D radiotherapy. From left to right: the dose distribution for patient 1 as planned (3D CRT; transversal and sagittal view), the 4D dose estimation as calculated by using the patient's 4D CT data and registration-based motion estimation therein, and a 4D dose estimation resulting from the application of the scaled 4D-MMM mean motion fields.



Figure 3. Differences between the planned and the accumulated dose for patient 1 (red = larger differences). The dose distributions compared are the same as shown in Figure 2. Left: Difference wrt. the dose accumulated by using the patient-specific 4D CT image sequence. Right: Difference wrt. the dose accumulated by application of the scaled 4D-MMM. It can be seen that the 4D-MMM-based dose accumulation yields an overestimation (or conservative risk assessment) of the dosimetric motion effects to be expected.

a dose outside the interval, this can be interpreted as indicating the need for redesigning the treatment plan. Corresponding dosimetric quantities for the three patients considered are summarized in Table 1. Again, it can be seen that values and consequences are widely in agreement, especially when comparing the dose distributions accumulated based on the patient-specific 4D CT image data and using the scaled 4D-MMM.

# 4. CONCLUSIONS

Model-based 4D dose calculation will not replace 4D CT imaging or diminish the need (and wish) for temporally resolved imaging modalities, but it promises to provide a reasonable risk assessment if only 3D CT is available in radiotherapy planning of lung tumors. This is primarily due to the fact that the 4D-MMM tends to overestimate tumor motion. It should nevertheless be noted that in particular cases it may happen that tumor motion and consequently dosimetric motion effects are underestimated (especially when applying the unscaled 4D-MMM; cf. results for patient 3). In the current study, combining the 4D-MMM with additional patient-specific spirometry measurements helped to obviate the risk of motion underestimation. The study, however, represents only a first feasibility study; further investigations with a larger number of patients and treatment plans will be necessary.

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