FULLY-DEFORMABLE PATIENT MOTION MODELS FROM CONE-BEAM CT FOR RADIOThERAPY APPLICATIONS

To cite this article: J Martin et al 2014 J. Phys.: Conf. Ser. 489 012034

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Fully-deformable patient motion models from cone-beam CT for radiotherapy applications

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Abstract. We propose a method to build a fully deformable motion model directly from cone-beam CT (CBCT) projections. This allows inter-fraction variations in the respiratory motion to be accounted for. It is envisaged that the model be used to track the tumour, and monitor organs at risk (OAR), during gated or tracked radiotherapy (RT) treatment of lung cancer. The method is tested on CBCT projections from a simulated phantom in two cases. The simulations are generated from a patient respiratory trace and associated CBCT scanner geometry. Without and with motion correction, $L^2$ norm maximum errors were reduced from 24.5 to 0.698 mm in case 1, and 20.0 to 0.101 mm in case 2, respectively.

1. Introduction

Accurate identification of targets prior to and during the course of radiotherapy are essential for state-of-the-art RT treatments [1]. Advances have enabled dose escalation, conformal sparing of OAR and non-uniform dose distributions. In treatments such as stereotactic ablative body RT, the dose is delivered in fewer fractions (3-5) and with a higher dose per fraction. Tumour respiratory motion is an important consideration during these treatments [2]. It is common to use 4DCT planning scans to identify the extent of respiratory motion and add a margin onto the delineated tumour region. Gated and tracked [3, 4] RT treatments allow this margin to be reduced, but rely on an accurate means of determining tumour position throughout the fraction.

We have previously published a method of generating a motion model from cine-CT [5] and to fit a model of tumour motion directly to a CBCT scan [6, 7]. The motion was related to a surrogate signal which can be monitored throughout the fraction and hence used to estimate tumour position. In this work the method is extended to non-rigid motion, allowing the respiratory motion of a number of anatomical structures to be modelled. This approach would allow other regions beyond the tumour, such as the organs at risk (OAR), to be tracked during treatment.

Modelling non-rigid deformations is achieved by the use of weighting arrays, which provide local variation of the deformation. It is envisaged that the weighting arrays be built from the 4DCT planning scans. Utilising planning scans may also allow the clinical planning delineations
to be adapted to the day of treatment. During a fraction of RT treatment the global parameters are fitted. These scale the local variation in each spatial dimension, hence accounting for inter-fraction changes in a patient-specific manner. Parameterising in this way (i.e. fitting the global parameters only during a fraction of treatment) reduces the complexity of the cost function, allowing the parameters to be found within seconds. In the method the iterative-based approach is described, including the form of the cost function to optimise. Once the motion model is fitted, only a new surrogate signal is needed to animate the OAR and tumour regions. This could be used, for example, to animate the 4DCT-derived clinical delineations, facilitating real-time monitoring during tracked RT treatments. Results are provided for two simulated cases, followed by conclusions and future work.

2. Modelling patient respiratory motion

During the CBCT scan, assume that the patient motion can be described by a series of deformations, $F_n$, of a motion-free image of the patient, $V_{ref}(x) : x \in \Omega$, where $\Omega$ is the region imaged during the CBCT scan. $n = 0, 1, \ldots, N - 1$ is an index corresponding to the time of each CBCT projection. Let the deformed patient volume $V_n$ be:

$$V_n(x) = V_{ref}(x + F_n(x)).$$ (1)

As with a previous publication [7], a surrogate signal is derived from an optical stereo-camera system (Vision RT, London, UK). A skin surface image is determined at the time of each projection, and the average height within a bounding box is used for the surrogate signal. The surrogate traces are normalised (mean subtracted; divided by standard deviation). The motion model used in this work is dependent on the surrogate signal, $s(n)$, and its temporal rate of change, $\dot{s}(n)$ [8]. As well as modelling hysteresis and changes in breath cycle length and depth during breathing, non-rigid deformations can be accounted for.

$$F_n(x) = s(n)D_1(x) \circ \phi_1 + \dot{s}(n)D_2(x) \circ \phi_2.$$ (2)

$\phi_1$ and $\phi_2$ are the motion model parameters (3D vectors). $\circ$ is an element-wise multiplication (Hadamard product). $D_1$ and $D_2$ are weighting arrays for $\phi_1$ and $\phi_2$, respectively. The weighting arrays are deformation fields, with a 3D vector at each point in the patient volume, $x$. These arrays provide spatially varying deformations, hence allowing non-rigid breathing motion to be modelled. The weighting arrays are static during parameter fitting. As only the global parameters are fitted, this facilitates a clinically feasible optimisation time of the cost function.

It is envisaged that the weighting arrays be determined prior to the fraction of treatment, for example using the 4DCT planning scan. $D_1$ could be constructed from registration of the end exhale and end inhale phases, and $D_2$ from mid-exhale and mid-inhale phases. A further registration of the mean 4DCT image to the CBCT reconstruction (on the day of treatment) would allow the weighting arrays to be aligned accordingly. If the final 4DCT to CBCT registration step can account for complex changes from planning, such as baseline shifts or tumour shrinkage, this method could also account for these changes. The weighting arrays determine relative motion of different parts of the anatomy whereas the motion model parameters control global changes to the magnitude of the overall LR, AP and SI motion. Hence some degree of inter-fraction variation can be accounted for by fitting the motion model parameters on the day of treatment.

3. Iterative approach to calculate motion compensated reconstruction (MCR) and motion model parameters

First presented in [6], an iterative approach is used to jointly determine the MCR and motion model parameters from the CBCT. An open-source, FDK-based software package
(www.openrtk.org) was modified to perform the MCRs. MCRs are performed by back-projecting each projection through a deformed volume. The deformation used was the inverse of the forward transformation estimated by the motion model for that particular projection.

Beginning with zero motion ($\phi_1 = \phi_2 = 0$), an MCR is calculated. This is then used as the reference volume and updates ($\delta \phi_1$ and $\delta \phi_2$) to the motion model parameters are determined. The updates were calculated via minimisation of a cost function, which alters the motion of the surrogate-animated MCR to produce projections more similar to the actual projections of the CBCT. The cost function takes the following form:

$$\delta \phi_1, \delta \phi_2 = \arg \min_{\delta \phi_1, \delta \phi_2} \left[ \sum_n \sum_{\text{pixels}} \left( (p_n - P_n(V_n)) - P_n(\nabla V_n \cdot \delta F_n) \right)^2 \right].$$  \hspace{1cm} (3)

where $P_n$ is the forward projection operator, $p_n$ is the $n$th projection of the CBCT and the update to the deformation

$$\delta F_n = s(n)D_1(x) \circ \delta \phi_1 + \delta(n)D_2(x) \circ \delta \phi_2.$$  \hspace{1cm} (4)

An algebraically expanded version of (3) was used for this work. This allowed the motion model parameters to be factored out of the summations, reducing optimisation time. The more compact version of the cost function is included here for brevity. Please see [7] for more information on deriving this expanded form.

The new motion model parameters can then be calculated via the update equation:

$$\phi_{\text{new}} = \phi + \delta \phi.$$  \hspace{1cm} (5)

Recalculating the MCR will give the updated MCR. Repeating the update steps will result in more accurate estimates of the motion model parameters and MCR.

4. Results
The method was initially tested on simulated data. A modified 3D-Shepp logan phantom was generated in MatLab within a 100 mm sided cube, constituting voxels of side length 1 mm. The phantom was animated and using a motion model with manually defined weighting arrays and a real patient surrogate trace, so as to produce realistic motion. A CBCT acquisition of the phantom was simulated using real scanner geometry. Two simulations are included. Both had relatively large SI and AP motion, with the maximum deformation being up to 25 and 20 mm for simulations 1 and 2, respectively. With the first case, the deformations were centred on the middle of the phantom. The second had deformations centred inside the middle of two centrally located ovals within the phantom.

The weighting arrays were manually defined to produce plausible respiratory-like deformations. For these preliminary experiments, the same weighting arrays were used for both generating the motion and fitting the motion model parameters. This was to determine if the parameters could be recovered if the weighting arrays were known. In both cases, the algorithm was terminated if the update caused the mean $l^2$ norm of the estimated motion to change by less than 0.4 mm, within the phantom region.

For the first simulation, the maximum $l^2$ norm of the motion estimation errors (relative to the mean position) was reduced from 24.5 to 0.698 mm, within the phantom region. The mean $l^2$ norm error was reduced from 3.01 to 0.157 mm. For the second simulation, the maximum $l^2$ norm error was reduced from 20.0 to 0.101 mm, with the mean $l^2$ norm error reduced from 0.969 to 0.0086 mm. Figure 1 shows the improvement in the MCR before and after fitting the parameters for both simulations. The best possible MCR is also given for reference. It can be seen that the results from the fitted model parameters are very similar to those from the known model parameters, and in both cases the motion artefacts have been removed from the reconstructions. Simulations 1 and 2 terminated after 9 and 3 iterations respectively.
5. Conclusions and future work
A method is presented to fit a non-rigid motion model directly to CBCT projections. Promising results are given for a simulated case undergoing two different types of motion. The authors intend to further develop the method, including obtaining results for actual patient data. The robustness of the method to artefacts present in actual CBCT data will be evaluated. An important part of this is determining the best method of generating the weighting arrays from the 4DCT planning scans. The most suitable method of their calculation and alignment to the CBCT reconstruction still needs to be determined and is currently being investigated by the authors.

Acknowledgments
James Martin gratefully acknowledges the support of the EPSRC funded UCL VEIV EngD programme, Vision RT and the 1851 Royal Commission Industrial Fellowship.

References