Real-time 3D tumor localization for lung IGRT using a single x-ray projection

1 Impact

We present a novel 2D/3D image registration method that can support real-time IGRT using a single x-ray projection image. Future IGRT with this registration technology can track the tumor and visualize the patient’s 3D deformations continuously throughout the treatment delivery with little x-ray dose.

2 Method

2.1 2D/3D Registration Framework

We describe PML-SKR’s 2D/3D registration framework. PML-SKR uses kernel regression (eq. 1) to interpolate the patient’s n 3D deformation parameters \( c = (c^1, c^2, \cdots, c^n) \) separately from the on-board projection images \( \Psi(\theta) \) where \( \theta \) is the projection angle. It uses a Gaussian kernel \( K_{M^i, \sigma^i} \) with the width \( \sigma^i \) and a metric tensor \( M^i \) on projection intensity differences to interpolate the patient’s \( i \)th deformation parameter \( c^i \) from a set of \( N \) training projection images \( \{P(I \circ T(c_\kappa); \theta) \mid \kappa = 1, 2, \cdots, N\} \) simulated at planning time. Specifically, the training projection image, \( P(I \circ T(c_\kappa); \theta) \), is the DRR of a CT deformed from the patient’s planning-time 3D mean CT \( I \) with sampled deformation parameters \( c_\kappa = (c^1_\kappa, c^2_\kappa, \cdots, c^n_\kappa) \). \( T \) and \( P \) are the warping and the DRR operators, respectively. \( P \) simulates the DRRs according to the treatment-time imaging geometry, e.g., the projection angle \( \theta \).

In the treatment-time registration, each deformation parameter \( c^i \) in \( c \) can be estimated with the following kernel regression:

\[
c^i = \frac{\sum_{\kappa=1}^{N} c^i_\kappa \cdot K_{M^i, \sigma^i}(\Psi(\theta), P(I \circ T(c_\kappa); \theta))}{\sum_{\kappa=1}^{N} K_{M^i, \sigma^i}(\Psi(\theta), P(I \circ T(c_\kappa); \theta))},
\]

(1)

\[
K_{M^i, \sigma^i}(\Psi(\theta), P(I \circ T(c_\kappa); \theta)) = \frac{1}{\sqrt{2\pi\sigma^i}} e^{-\frac{d^2_{M^i}(\Psi(\theta), P(I \circ T(c_\kappa); \theta))}{2\sigma^i}}
\]

(2)

\[
d^2_{M^i}(\Psi(\theta), P(I \circ T(c_\kappa); \theta)) = (\Psi(\theta) - P(I \circ T(c_\kappa); \theta))^TM^i(\Psi(\theta) - P(I \circ T(c_\kappa); \theta)),
\]

(3)

where \( K_{M^i, \sigma^i} \) is a Gaussian kernel (kernel width= \( \sigma^i \)) that uses a Riemannian metric \( M^i \) in the squared distance \( d^2_{M^i} \) and gives the weights for the parameter interpolation in the regression.
3 Results

Figure 1 shows that PML-SKR reduces the minimum errors produced by kernel regressions that use the Euclidean metric ($M^i = I$).

2.2 Metric Learning and Kernel Width Selection

PML-SKR learns a metric tensor $M^i$ with a corresponding kernel width $\sigma^i$ for the patient’s $i^{th}$ deformation parameter $c^i$ using a Leave-One-Out (LOO) training strategy. At planning time, it samples a set of $N$ deformation parameter tuples $\{c_\kappa = (c_1^\kappa, c_2^\kappa, \cdots, c_n^\kappa) \mid \kappa = 1, 2, \cdots, N\}$ to generate training projection images $\{P(I \circ T(c_\kappa); \theta) \mid \kappa = 1, 2, \cdots, N\}$ where their associated deformation parameters are sampled uniformly within three standard deviations of the values observed in the RCCTs. For each deformation parameter $c^i$ in $c$, PML-SKR finds the best pair of the metric tensor $M^i$ and the kernel width $\sigma^i$ that minimizes the sum of squared LOO regression residuals among the set of $N$ training projection images:

$$M^{i^*}, \sigma^{i^*} = \arg \min_{M^i, \sigma^i} \sum_{\kappa=1}^{N} \left( c_{\kappa}^i - \hat{c}_{\kappa}^i (M^i, \sigma^i) \right)^2, \quad (4)$$

$$\hat{c}_{\kappa}^i (M^i, \sigma^i) = \frac{\sum_{\chi \neq \kappa} c_{\chi}^i \cdot K_{M^i, \sigma^i}(P(I \circ T(c_\kappa); \theta), P(I \circ T(c_\chi); \theta))}{\sum_{\chi \neq \kappa} K_{M^i, \sigma^i}(P(I \circ T(c_\kappa); \theta), P(I \circ T(c_\chi); \theta))}, \quad (5)$$

where $\hat{c}_{\kappa}^i (M^i, \sigma^i)$ is the estimated value for parameter $c_{\kappa}^i$ interpolated by the metric tensor $M^i$ and the kernel width $\sigma^i$ from the training projection images $\chi$ other than $\kappa$.

3 Results