A Kernel-based Framework for Intra-fractional Respiratory Motion Estimation in Radiation Therapy

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Abstract

In radiotherapy, tumor tracking allows the beam to follow the respiration-induced tumor motion. Motion models [1] have been investigated to estimate dense internal displacement fields from an external surrogate signal, such as range imaging [2][3]. With increasing surrogate complexity, we propose a motion estimation framework based on kernel ridge regression to cope with high-dimensional domains. The approach was initially validated on five patient datasets, each consisting of a planning and a follow-up 4-D CT. Mean residual error was 2.73 ± 0.25 mm, but varied greatly.

Introduction

Respiratory motion affects external beam radiation therapy

- Dose distribution from treatment plan based on CT image
- Motion: dislocation of target / survival of malignant cells

Motion estimation for gating / tracking

- Based on implanted fiducial and surface markers
- Only sparse information

High-dimensional data

- Dense information, but computationally challenging

Materials and Methods

Data & Evaluation

- Retrospective evaluation on 5 patient data sets (**Fig. 1**)
- Planning (PCT) & follow-up (FCT) 4-D CTs ($1 \times 1 \times 2\,mm^3$)

Data Matrices

- Internal: B-spline non-rigid registration on 4-D CT and cropped to internal region of interest; $\{\boldsymbol{t}_1, \dots, \boldsymbol{t}_n\} \in \mathbb{R}^{d_t}$
- Surrogate: motion fields interpolated at reference surface extracted from end-exhale volume; $\{\boldsymbol{s}_1, \dots, \boldsymbol{s}_n\} \in \mathbb{R}^{d_s}$

  Both stored column-wise in $\boldsymbol{T} \in \mathbb{R}^{d_t \times n}$ and $\boldsymbol{S} \in \mathbb{R}^{d_s \times n}$

Kernel Ridge Regression (KRR)

- Objective function: $\arg\min_{\boldsymbol{W}} \left(\frac{1}{2} \|\boldsymbol{W}\boldsymbol{S} - \boldsymbol{T}\|_F^2 + \alpha \frac{1}{2} \|\boldsymbol{W}\|_F^2 \right)$
- Prediction: $\boldsymbol{t}_{pred} = \boldsymbol{T}\,(\boldsymbol{K} + \alpha\,\boldsymbol{I}_n)^{-1} \boldsymbol{\kappa}(\boldsymbol{s}_{new})$ (1)
  - $\boldsymbol{K}_{ij} = \boldsymbol{\phi}(\boldsymbol{s}_i)^\top \boldsymbol{\phi}(\boldsymbol{s}_j)$ Gram matrix of mapped samples
  - $\boldsymbol{\kappa}(\boldsymbol{s}_{new})_i = \boldsymbol{\phi}(\boldsymbol{s}_i)^\top \boldsymbol{\phi}(\boldsymbol{s}_{new})$ Kernel response for new surrogate
- Implicit mapping $\boldsymbol{\phi}$ expressed only in terms of inner products
- Supports non-linear kernels, e.g. Gaussian & polynomial

Generalization using an Active Shape Model (ASM) [4]

- Omit redundant information by decomposing training sample $\boldsymbol{T}$ into mutually orthogonal modes of variation using PCA
- Data point $\boldsymbol{t}$ expressed in terms of new basis

$$\boldsymbol{t} = \bar{\boldsymbol{t}} + \boldsymbol{M}_t \boldsymbol{f}_t + \boldsymbol{\epsilon}$$

  - $\boldsymbol{M}_t = [\boldsymbol{v}_1, \boldsymbol{v}_2, \dots, \boldsymbol{v}_{p_t}] \in \mathbb{R}^{d_t \times p_t}$, the first p_t eigenvectors
  - $\bar{\boldsymbol{t}}$ data consensus, $\boldsymbol{f}_t \in \mathbb{R}^{p_t}$ feature vector, $\boldsymbol{\epsilon}$ residual variance
- Instead of data matrices, Eqn. (1) can be computed using the set of features $\boldsymbol{F}_T \in \mathbb{R}^{p_t \times n}$ and $\boldsymbol{F}_S \in \mathbb{R}^{p_s \times n}$

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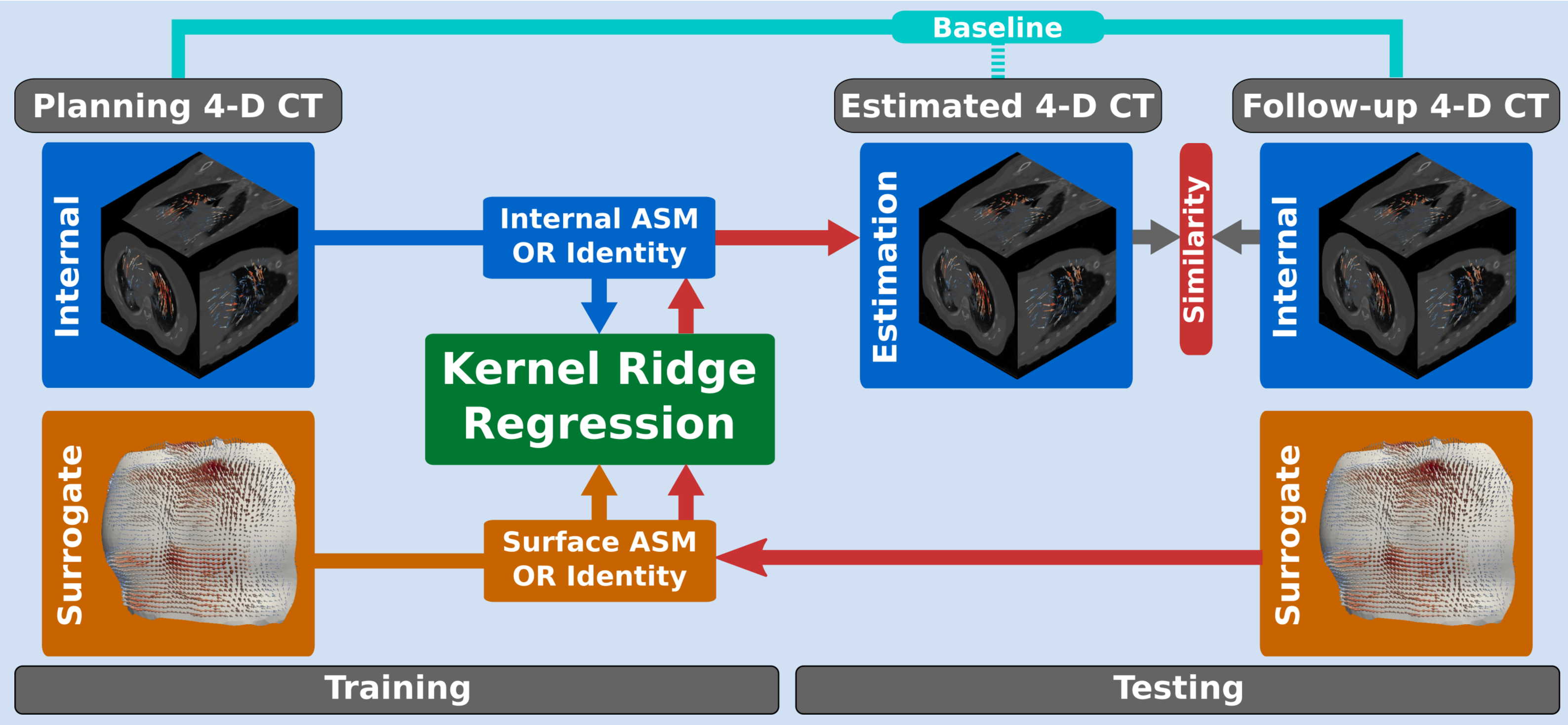

Figure 1: Workflow of the motion estimation pipeline and evaluation. Both PCT and FCT provide internal deformation and surface information for training and evaluation, respectively.

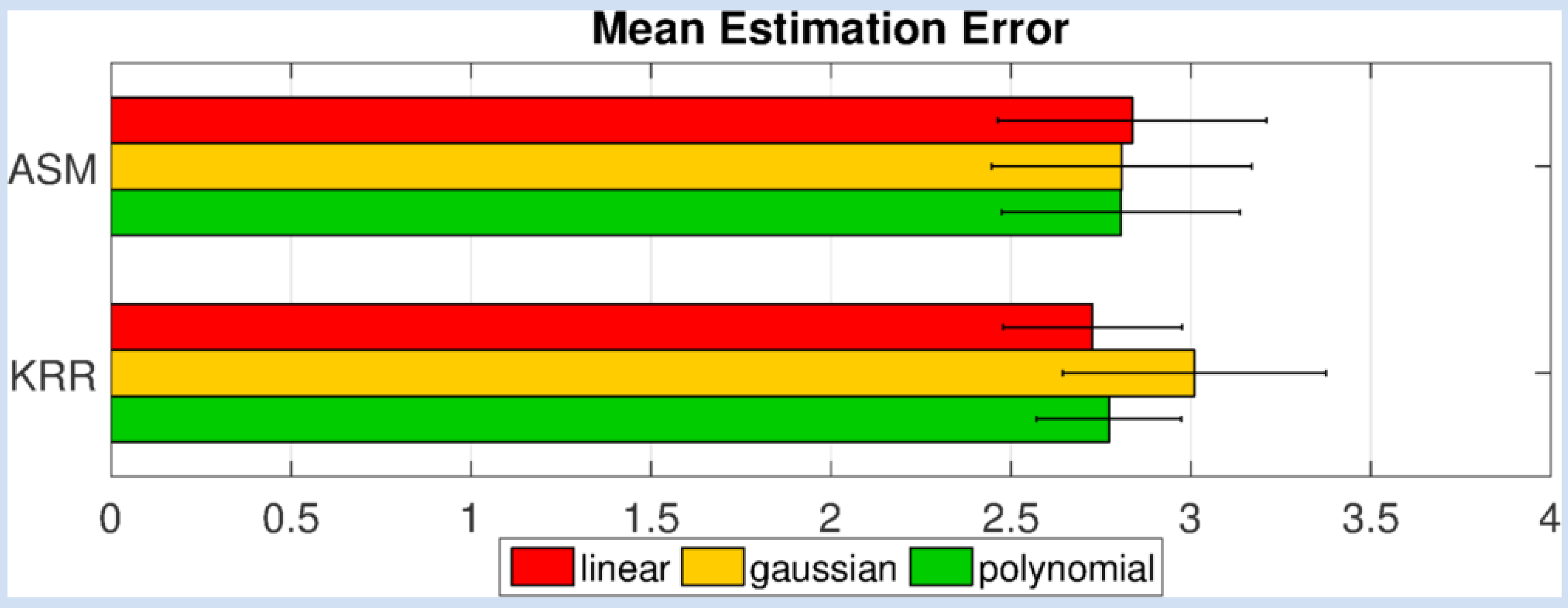

Figure 2: Mean error and standard deviation over all patients based on surface surrogate with (ASM) and without (KRR) generalization using an Active Shape Model.

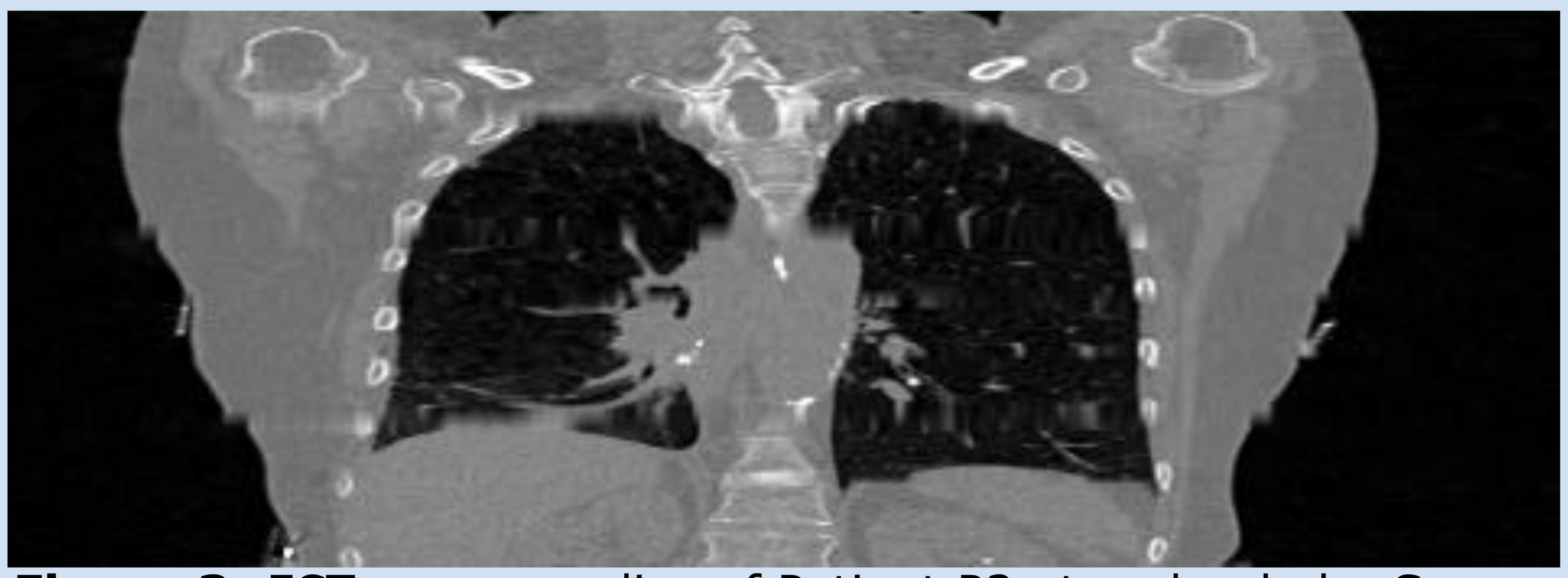

Figure 3: FCT coronary slice of Patient P2 at end-exhale. Severe artifacts are visible near the diaphragm and the top of the lung, prohibiting accurate estimation of internal deformation fields.

Results and Discussion

Results (**Fig. 2**)

- Reference mean magnitude: 3.57 ± 0.43 mm
- Proposed methods: 2.73 ± 0.25 mm estimation error

Discussion

- No improvement for non-linear mappings
- Phase reconstruction difference
  - KRR: weighted sum of observed training samples
  - ASM: linear combination of eigenvectors
- Artifacts dramatically affect the estimation (**Fig. 3**)
- Major influence of the baseline registration

Conclusions

- A-priori motion model operating directly on observed surrogate data w/ or w/o dimensionality reduction

Future Work

- Further evaluation on additional data sets
- Improvement of baseline registration
- Incorporation of live feedback into the model

References

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