Combination of Markerless Surrogates for Motion Estimation in Radiation Therapy

T. Geimer[1,2], M. Unberath[1,2], O. Taubmann[1,2], C. Bert[2,3], A. Maier[1,2]
[1] Pattern Recognition Lab, Friedrich-Alexander-University Erlangen-Nuremberg, Germany
[2] Graduate School in Advanced Optical Technologies, Erlangen, Germany
[3] University Hospital Erlangen, Radiation Oncology, Erlangen, Germany

Keywords: Motion Modeling, X-ray, Range Imaging, Dimensionality Reduction, Regression

Purpose

Respiratory motion drastically affects dose profiles in radiation therapy and needs to be compensated. Usually the internal motion is inferred from a correlated external surrogate [1][2]. We propose an image-based model to estimate internal motion fields from X-ray fluoroscopy using dimensionality reduction and regression techniques. Further, we present results of an early study investigating possibilities to incorporate multiple surrogates, range imaging [3] and fluoroscopy, into the estimation process.

Methods

Recently, Taubmann *et al.* [3] proposed an approach to model dense deformation fields of both the internal organs and the external surface based on 3-D MRI sequences. Employing dimensionality reduction and multilinear regression the features of the internal motion model $\boldsymbol{\Phi} = [\boldsymbol{\phi}_1, \dots, \boldsymbol{\phi}_n]^T \in \mathbb{R}^{n \times l}$ were estimated from the surface motion model features $\boldsymbol{\Sigma}_{\mathrm{RI}} = \left[\boldsymbol{\sigma}_{\mathrm{RI}_1}, \dots, \boldsymbol{\sigma}_{\mathrm{RI}_n}\right]^T \in \mathbb{R}^{n \times f_{\mathrm{RI}}}$, where n is the number of respiratory phases and l, f_{RI} are the chosen feature space dimensionalities. Correlation between the features is understood as a multivariate multilinear regression (MLR) problem.

Using 4-D CT data, we expand on this approach introducing fluoroscopy images as a surrogate. Digitally Reconstructed Radiographs (DRR) [4] are used for training purposes. Assuming that respiration is the main mode of variation among the images, the first few principal components of the set of all vectorized projection images are highly correlated to the breathing signal [5]. Principal Component Analysis (PCA) finally yields the feature matrix $\boldsymbol{\Sigma}_{\mathrm{FL}} = \left[\boldsymbol{\sigma}_{\mathrm{FL}_1}, \dots, \boldsymbol{\sigma}_{\mathrm{FL}_n}\right]^T \in \mathbb{R}^{n \times f_{\mathrm{FL}}}$, where f_{FL} is the number of principal components for the fluoroscopy model.

In some cases, multiple surrogates can be acquired during treatment. We consider possibilities of combining information from range imaging and fluoroscopy. The information added by the second surrogate may be used to improve the estimation or compensate for one surrogate failing. To this end, a combined low-dimensional feature vector of both surrogates is created:

$$\boldsymbol{\sigma}_{\mathrm{CB}_i} = \begin{bmatrix} \boldsymbol{\sigma}_{\mathrm{RI}_i} \\ \boldsymbol{\sigma}_{\mathrm{FL}_i} \end{bmatrix} \in \mathbb{R}^{(f_{\mathrm{RI}} + f_{\mathrm{FL}}) \times 1}.$$

Then, the feature matrix $\boldsymbol{\Sigma}_{CB} = \left[\boldsymbol{\sigma}_{\mathrm{CB}_1}, \dots, \boldsymbol{\sigma}_{\mathrm{CB}_n}\right]^T \in \mathbb{R}^{n \times (f_{\mathrm{RI}} + f_{\mathrm{FL}})}$ is used as the surrogate input for regression. The number of retrievable internal features is determined by the column rank r of $\boldsymbol{\Sigma}_{\mathrm{CB}}$. If the feature vectors $\boldsymbol{\delta}_{\mathrm{RI}_i}$ and $\boldsymbol{\delta}_{\mathrm{FI}_i}$ are linearly independent, suggesting that they contain partially unique information, $r \leq f_{\mathrm{RI}} + f_{\mathrm{FL}}$ can exceed the single surrogate bounds. This observation indicates that it may be possible to correctly estimate multiple target features while only relying on a few surrogate features that are shown to correlate well (see Table 1).

The approach was evaluated on nine 4-D CT patient data sets consisting of ten volumes each. Registration provides nine deformation fields describing distinct motion states. Estimation accuracy was assessed in a leave-one-out study for each data set, where each phase was subsequently chosen as the test phase. We also excluded the two neighboring phases from training to prevent bias. The remaining six phases were used to train the correspondence models. Accuracy was defined as the root-mean-square error w.r.t. vector magnitudes between the estimated deformation field and the ground truth deformation field of the test phase.

Results

Table 1 shows correlation results for three out of nine patients. Exemplary for $l, f_{\mathrm{RI}}, f_{\mathrm{FL}} = 3$ the first to third PCA scores were compared. While the first component correlates well with the internal model, the second one is varying significantly, with the third one mostly correlating poorly. Fig. 1 shows the mean estimation error over nine data sets for the three approaches surface (RI), fluoroscopy (FL), and their combination (CB). Fluoroscopy outperformed the surface with the lowest error of 0.67 ± 0.33 mm for $l = 2$. However, accuracy did not improve with higher internal model dimension. Combining two surrogates in the proposed manner did not yield consistent improvement. For $f_{\mathrm{RI}}, f_{\mathrm{FL}} = 1$ both features represent the respiratory phase making them redundant. Thus, for a $(1/1)$ combined feature vector the rank-deficient surrogate matrix is unable to explain two internal features. In contradiction to the other results, estimating $l = 2$ internal features from a $(2/2)$ or higher combined feature vector is promising with the best overall estimation of 0.62 ± 0.28 mm, indicating that a combination of surrogates is useful under certain circumstances. The mean error without compensation was 2.3 ± 0.70 mm.

Conclusion

The combination of surrogates did yield improvements, however they were only minor. This suggests that for future work more sophisticated approaches need to be explored in order to extract mutually exclusive information from the surrogates. Further, a detailed rank analysis of the regression matrix can help identify conditions in which a combined approach is useful.

References

[1] J R McClelland et al. (2013) Respiratory motion models: A review. Med Image Anal, 17(1):19–42

[2] M Wilms et al. (2014) Multivariate regression approaches for surrogate-based diffeomorphic estimation of respiratory motion in radiation therapy. Phys Med Biol, 64(5)

[3] O Taubmann et al. (2014) Prediction of Respiration-Induced Internal 3-D Deformation Fields From Dense External 3-D Surface Motion. CARS 2014, pp. 33 – 34

[4] G W Sherouse et al. (1990) Computation of Digitally Reconstructed Radiographs for Use in Radiotherapy Treatment Design, Int J Radiat Oncol, 18(3):651 – 658

[5] P Fischer et al. (2014) Real-Time Respiratory Signal Extraction from X-Ray Sequences using Incremental Manifold Learning. ISBI 2014, pp. 915–918

Table 1: Pearson's correlation coefficient of the internal model features and the two surrogate features of the first three patient data sets.

	Pat1			**Pat2**			**Pat3**		
component	1	2	3	1	2	3	1	2	3
$\lvert\mathrm{cor}(\boldsymbol{\phi}, \boldsymbol{\sigma}_{\mathrm{RI}})\rvert$	0.98	0.85	0.59	0.99	0.99	0.97	0.96	0.92	0.96
$\lvert\mathrm{cor}(\boldsymbol{\phi}, \boldsymbol{\sigma}_{\mathrm{FL}})\rvert$	1.0	0.99	0.57	0.99	0.91	0.88	1.0	0.45	0.39
$\lvert\mathrm{cor}(\boldsymbol{\sigma}_{\mathrm{RI}}, \boldsymbol{\sigma}_{\mathrm{FL}})\rvert$	0.97	0.85	0.15	1.0	0.94	0.91	0.96	0.36	0.20

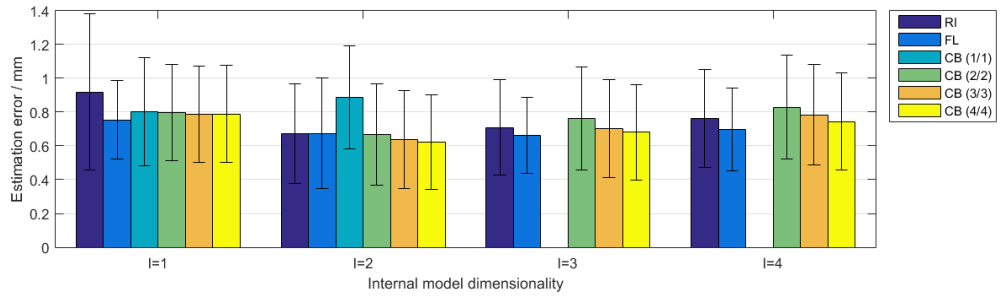

Fig. 1: Mean error and standard deviation for estimation based on single and multiple surrogates over nine patient data sets. $CB(x/x)$ denotes estimation of l internal features from a combination of x features of each surrogate (with $l \geq 3$ being underdetermined for $x = 1$).