Prediction of Respiration-Induced Internal 3-D Deformation Fields From Dense External 3-D Surface Motion

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Purpose

Respiratory motion is a challenge for image-guided procedures concerning the thorax or abdomen such as radiation therapy or cardiac interventions. A common approach to motion compensation is predicting internal target displacements from an external surrogate signal.
Recent methods employ range imaging to generate high-dimensional breathing surrogates. However, they e.g. rely on heuristic surface partitioning [1] or do not consider internal motion directly [2]. We propose a statistical framework using dimensionality reduction and multilinear regression to predict internal deformation fields from dense body surface motion.

Methods

From a sequence of 3-D MRI images in different respiratory states [3] we model deformations both internally, i.e. of structures inside the body, and externally, of the body surface. We then relate these models to obtain a joint model suited for internal motion prediction.
To train the internal model, we non-rigidly register all phases to a reference phase and perform dimensionality reduction on the resulting deformation fields. For registration, we employ a variational curvature-regularized method [4]. The resulting deformation fields are cropped to an internal region of interest (ROI). Describing motion by a model allows us to be more efficient and to prevent overfitting. The dimensionality reduction needs to be invertible as we will reconstruct deformation fields from the low-dimensional features. We use principal component analysis (PCA) as the basis for our internal model. In a second step, we model the external body surface motion. Acquiring the body surface with a range imaging (RI) system simultaneously with tomographic imaging is difficult in practice. Therefore, we extract the surface motion from the 3-D images. The surface is segmented in the reference phase with a ray-casting based approach. Postprocessing of the resulting mesh is necessitated by artifacts due to undersampling and fat saturation in our cardiac MRI protocol. To obtain the surface motion, the volumetric deformation fields computed earlier are interpolated at the mesh vertices. In contrast to the internal model, we are not interested in reconstructing deformation fields, which leaves us with a broader range of viable dimensionality reduction methods. Apart from PCA, we have tested two nonlinear techniques: Isomap and Kernel PCA.
Finally, external-internal correlation is formulated as a multivariate multilinear regression between the feature spaces of both models and solved by ordinary least squares estimation. For prediction, the surface motion is mapped to the feature space by out-of-sample extension of the external model. After performing regression to obtain the corresponding internal feature, a deformation field for the ROI can be reconstructed using the internal model.
We have evaluated our method on synthetic data derived from the 4-D extended cardiac-torso (XCAT) phantom [5] and time-resolved cardiac MRI images [3] from 6 healthy volunteers (P1 through P6). For each subject-specific data set, we choose one phase as the test set and also exclude the two nearest remaining phases from training to reduce bias. Prediction is performed for the test phase and error statistics are reported w.r.t. the vector magnitudes of the difference between the predicted deformation field and the ground truth obtained by registration or, in the case of XCAT, interpolation of sparse motion on a regular grid [5].

Results

Regardless of the chosen method, the synthetic data set is predicted almost perfectly. For MRI data, we achieve a maximum prediction error of 0.42 mm in the best configuration, given a

median magnitude of the ground truth deformation field of 3.91 mm. In our use case, which suffers from a small amount of training samples, PCA clearly outperforms the nonlinear methods. In Fig. 1, the effect of varying surface coverage is shown. Small areas yield equal or worse results compared to the full surface. Given wide coverage, though, a random 10% of the vertices offer the same accuracy. Fig. 2 covers different smoothness levels of the registration, demonstrating a trade-off. Less smoothing allows representing finer details, but also causes artifacts that impair prediction accuracy. Using a GPU-based implementation, we achieve runtimes of 5-10 ms for predicting internal motion from the surface motion surrogate.

Conclusion

Our approach shows promising results regarding the accuracy and performance of prediction of internal displacements from dense external surface motion. We demonstrate that a larger surface coverage can improve upon localized external surrogates and quantify how much prediction accuracy improves with smoother deformation fields. Future work will have to focus on a clinical setting with range imaging and mesh registration to provide the surrogate.

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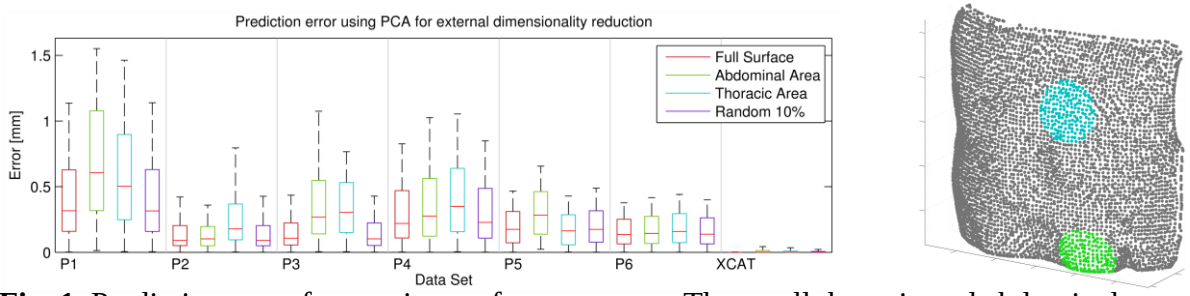

Fig. 1. Prediction error for varying surface coverage. The small thoracic and abdominal areas (radii ca. 3.3 cm each) are exemplarily shown on the right for P1.

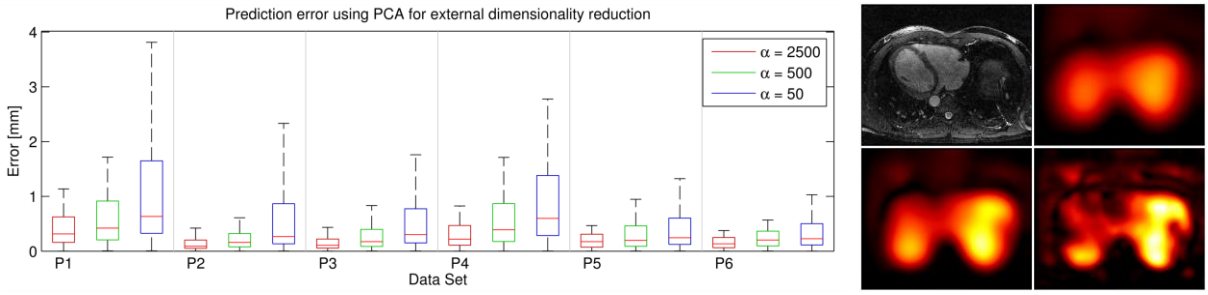

Fig. 2. Prediction error for different smoothness levels of the registration. Parameter α controls the regularizer strength (cf. [4]). Ground truth motion with decreasing smoothness (α = {2500, 500, 50}) is shown on the right. Brighter areas indicate larger magnitudes.